Evaluating the Impact of Public Charging Reliability on Electric Vehicle Adoption

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A thesis
submitted in partial fulfillment of the
requirements for the degree of

Master of Science in Civil Engineering

University of Washington
2024

Committee:
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Program Authorized to Offer Degree:
Civil and Environmental Engineering

University of Washington

Abstract

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Substantial investments are being directed toward the development of public electric vehicle (EV) charging infrastructure, but there is growing concern regarding the reliability of these chargers. While several recent studies have documented instances of unreliable chargers, there is no established understanding of the impact of such reliability issues on EV adoption rates. This research aims to fill this gap by examining the influence of perceived reliability of public charging stations on the propensity of potential buyers to adopt electric vehicles. Leveraging data collected from an original nationwide survey conducted between March and April 2024, this study employs a comprehensive analytical framework, combining a two-stage least squares approach with an integrated choice and latent variable model. The findings underscore the critical role of robust public charging infrastructure in fostering EV adoption. Specifically, the study quantifies the ramifications of low perceptions of reliability based on purchase price, operating costs, range, and charging availability, providing insights into the extent to which poor reliability can impede EV market share growth, and offering justification for investments into improving the reliability of public chargers.

1. INTRODUCTION

1.1. Motivation

Technological advancements and supportive government policies have spurred the growth of the electric vehicle (EV) market in the United States. From 2022 to 2023, the EV market share expanded from 5.9% to 7.6% (Rika, 2024). Furthermore, 16 states have mandated that all new light-duty vehicles sold emit zero-emissions by 2035, accounting for 36.4% of the light-duty new vehicle registrations market (CARB, 2024). However, to sustain market growth, EVs must become acceptable to all consumers, and despite early trends, the transition to electric vehicles faces significant challenges as the market moves beyond early adopters (Alanazi, 2023; Pamidimukkala et al., 2024).

A key obstacle repeatedly identified as a barrier to widespread adoption is the development of charging infrastructure. Prior work has highlighted the importance of the availability of public chargers (Egnér & Trosvik, 2018; Mersky et al., 2016; Okoma, 2023; Sierzchula et al., 2014). However, in recent years, there have been increasing concerns about the reliability of these chargers. Countless reports in the media highlight unreliable public charging stations, emphasizing the challenges faced during long road trips (Dvorak, 2023; MotorTrend, 2023; Wolfe, 2022). As negative experiences accumulate and become more widely known, they may deepen potential buyers' reluctance to purchase an EV. There is a clear need for public charging infrastructure to facilitate the transition to electric vehicles, but there remains a significant gap in understanding how perceptions of public charging reliability might impact EV adoption rates.

The goal of this thesis is to examine how perceptions of public charging reliability influence EV purchase decisions among people who do not yet have an EV. We provide the first analysis of the causal impact of public charging reliability on EV purchase intentions. To do so, we employ an integrated choice and latent variable (ICLV) model with a two-stage least-squares (2SLS) approach to analyze stated preference data from a nationwide survey collected in March-April 2024. Our findings underscore the critical importance of public charging reliability in EV adoption, indicating that not improving current conditions will reduce the market share of EVs. These insights aim to provide policymakers and stakeholders with an understanding of the urgency of improving charging infrastructure to achieve widespread adoption and meet environmental goals.

1.2. Outline of Research

The rest of this thesis is organized as follows. Section 2 provides an overview of the literature relating to EV adoption, measures of public charging reliability, and the current understanding of public charging reliability. Section 3 presents the survey design. Section 4 presents the analytic framework used in this thesis. Section 5 contains the model results, and Section 6 concludes the thesis with a discussion of the important findings and identifies future research directions.

2. LITERATURE REVIEW

2.1. Factors Affecting EV Adoption

The literature on the determinants of EV adoption continues to expand, shedding light on both the driving forces and barriers to purchasing EVs. According to Liao et al. (2017)'s review, these factors can be categorized into five broader categories: psychological considerations, financial considerations, technical considerations, policy considerations, and infrastructure considerations. Psychological considerations evaluate how various attitudes and beliefs affect EV adoption. These attitudes include openness to new technologies (Bockarjova et al., 2014; Helveston et al., 2015) and pro-environmental attitudes (Hackbarth & Madlener, 2013). Recent reports from consumer research firms have found that environmental protection remains a primary motivator for both current EV owners and potential buyers, as people believe transitioning to EVs can reduce their carbon footprint (Consumer Reports, 2022a; Jackson et al., 2023; Plug In America, 2023).

Alongside environmental considerations, financial factors significantly influence the decision-making process between electric and conventional vehicles. Liao et al. (2017) reviewed 26 studies and found that across all of them, increasing purchase price had a negative effect on EV purchases. Another important financial factor potential buyers consider is operating cost, and many researchers have used stated preference experiments to assess the magnitude of the effect of operating costs on EV adoption (Forsythe et al., 2023; Helveston et al., 2015; Huang et al., 2021; Zou et al., 2020). Some studies have also examined maintenance costs (Liao et al., 2017), highlighting the comprehensive financial evaluation buyers conduct when considering EV purchases.

Among the technical considerations, range has long been recognized as a critical factor in the adoption of various alternative fuel vehicles, including biofuel vehicles (Hackbarth & Madlener, 2013; Valeri & Danielis, 2015), fuel-cell vehicles (Hackbarth & Madlener, 2013; Hoen & Koetse, 2014), natural gas vehicles (Hackbarth & Madlener, 2013), and electric vehicles (Forsythe et al., 2023; Qian & Soopramanien, 2011; Tanaka et al., 2014; Valeri & Danielis, 2015; Zou et al., 2020). In general, these studies have found that greater range capacities are correlated with higher willingness to purchase EVs. Other studies have also focused on understanding EV drivers' experience with range, looking at how drivers' knowledge of range dynamics and risk tolerance influence their charging behaviors (Franke & Krems, 2013; Pan et al., 2019; Sprei & Kempton, 2024). Other technical factors affecting EV adoption include recharging time, acceleration time, and brand and diversity (Liao et al., 2017).

Policy factors have been assessed on a global scale, particularly focusing on how monetary incentives influence EV adoption. For example, Münzel et al. (2019) analyzed registration data and monetary incentives in 32 European countries including France, Norway, and the United Kingdom. Their findings demonstrated a strong and positive correlation between plug-in EV shares and financial incentives. In the United States, Jenn et al. (2018) assessed the effectiveness of promoting EV adoption, revealing that rebates and tax credits were both effective in encouraging EV adoption. These studies collectively emphasize the strong relationship between policy incentives and the increased adoption of EVs.

Of the numerous factors influencing EV adoption, recent reports from consumer research firms consistently highlight the lack of public charging infrastructure as the primary reason for potential EV buyers rejecting EV ownership (Cox Automotive, 2023; J.D. Power, 2023). In the academic literature, charging availability is a common attribute in stated preference surveys evaluating EV preferences, measured across various scales such as the percentage of available gas stations (Hackbarth & Madlener, 2013; Qian & Soopramanien, 2011; Tanaka et al., 2014; Mau), distance from home to charging station (Rasouli & Timmermans, 2014; Valeri & Danielis, 2015; Zou et al., 2020), and detour time than to a gas station (Bockarjova et al., 2014; Chorus & Kroesen, 2014; Hoen & Koetse, 2014). Studies have revealed a positive correlation between charging infrastructure availability and EV adoption rates at various scales, from national to municipal levels (Egnér & Trosvik, 2018; Mersky et al., 2016; Okoma, 2023; Sierzchula et al., 2014). The increase in public chargers not only enhances the practicality of EV driving but also signifies a shift in social norms, making EV purchase more acceptable to prospective buyers (White et al., 2022).

While access to public charging is crucial, reliance on an unreliable public charging station fails to address the fundamental concerns about EV charging. Charger failures, especially during long-distance travels, in areas with sparse charging infrastructure, or for users lacking home charging access, can lead to severe consequences (Karanam & Tal, 2023). In its current state, public charging reliability could pose a large issue to widespread EV adoption. A 2022 audit in the San Francisco Bay Area found that nearly 28% of direct-current fast charging (DCFC) stations were unusable, attributed to a variety of reasons – unresponsive screens, payment system failures, charge initiation failures, connectivity failures, or physical issues with the connectors (Rempel et al., 2022). A 2022 survey conducted by J.D. Power found that over a 5-month study period, 20% of survey respondents couldn't charge their vehicle at a charging station, with the majority of them blaming station malfunctions or out of service chargers (J.D. Power, 2022). In 2023, this increased to 21% (Tucker, 2023).

Figure 1 from a Plug In America report (2023) depicts a notable decline in satisfaction with public chargers from 2022 to 2023, attributed to a variety of issues, from broken chargers to high costs of charging. Kurani & Ogunmayin (2023) further emphasize that while early adopters may tolerate the inconvenience of searching for available or functional chargers, achieving widespread adoption requires addressing this challenge. Improving the reliability of charging infrastructure is a top federal priority with $100M allocated by the Biden administration to improve and expand public charging stations (Joint Office of Energy and Transportation, 2023).

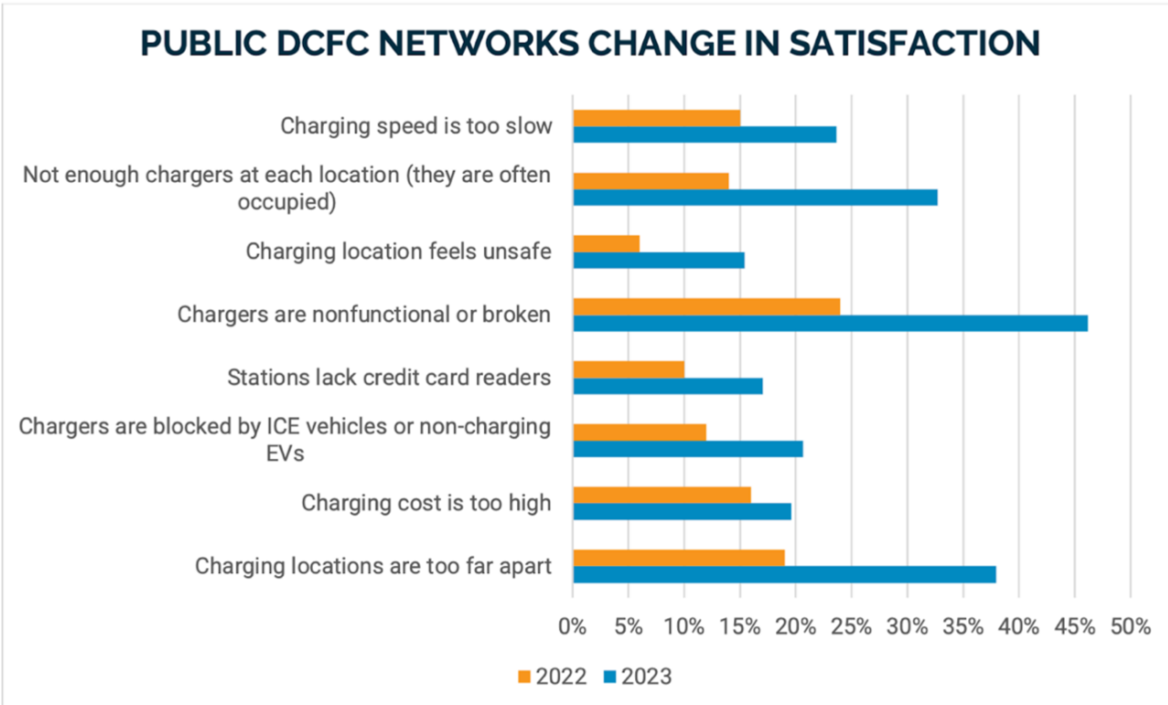

Figure 1 Public DCFC networks change in satisfaction (Plug In America, 2023)

2.2. Defining and Measuring Public Charging Reliability

Many different metrics have been implemented to address the growing dissatisfaction with public charging reliability and to deepen the understanding of the user charging experience. These measures can be categorized as either objective (based on observation) or subjective (based on personal experiences). Table 1 provides an overview of the metrics used in the literature and their respective classifications.

The objective measures of charging reliability serve as fundamental indicators for assessing the operational status of chargers and devising strategies for their maintenance and improvement. In contrast, the subjective measures wield significant influence over actual behaviors related to EVs. According to the Theory of Planned Behavior, individuals' actions are directly influenced by their intentions, which, in turn, are shaped by their perceived ability to execute the intended behavior (Ajzen, 1991). In the context of EV chargers, this perceived ability directly relates to individuals' decisions to charge a vehicle; in other words, the belief "I can charge an EV" directly influences the decision "I will charge an EV". Additionally, perceived reliability may not always align with actual charging capabilities which are captured by objective reliability measures. Hence, understanding people's perceptions of reliability (rather than evaluating the operational status) is pivotal for predicting their behavior, and in understanding how to ensure widespread EV adoption. Figure 2 outlines the Theory of Planned Behavior as it applies to public charging reliability.

TABLE 1 Public charging reliability metrics and their objective or subjective classifications

	Measure of Public Charging Reliability	**Source**
	Charger availability	2, 3, 7, 8
	Number of ports	1
	Charger accessibility (clear pathways, weather protection, manageable cables, etc.)	6
	Hardware issues	5, 6
	Charging issues	6
	Charging efficiency	3, 5, 7, 8
	Uptime	4
	Failure rate (number of failed charge cycles)	4
	Utilization (number of sessions per month, charging hours per month, plug-in time, etc.)	4, 6
	Mean time between failure	4
	Vehicle failure rate	4
	Mean time to repair	4
	Reviews and feedback from ChargeHub customers	1
	Ease of finding the charger	3, 4, 7, 8
	Payment (initiation, options, ease)	3, 4, 5, 7, 8, 9
Subjective Measures	Ease of use	2, 3, 8
	Functionality	2, 3
	Comfort	2, 8
	Satisfaction	10

Sources:

1.
2. Fabianek & Madlener, 2023
3. J.D. Power, 2023
4. Alexander et al., 2023
5. Okoma, 2023
6. Mogile Technologies, Inc., 2022
7. Plug In America, 2023
8. Consumer Reports, 2022b

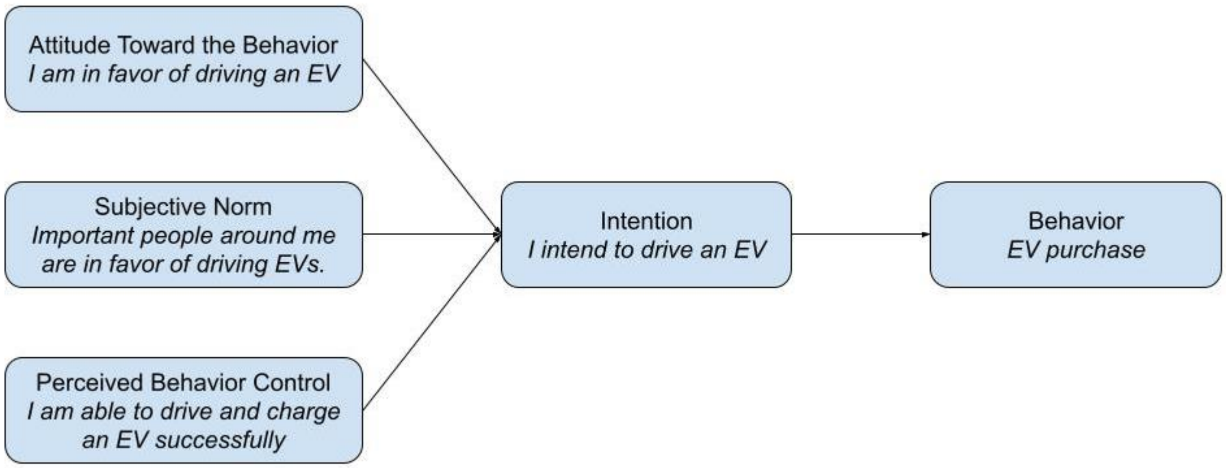

Figure 2 Theory of Planned Behavior applied to public charging reliability

2.3. Current Understanding of the Effect of the Public Charging Reliability on EV Adoption

In various transportation contexts, perceived reliability is a crucial attribute. For example, the perceived reliability of travel time affects travelers' choices of mode, route, and departure time (Carrion & Levinson, 2012; G. Li et al., 2022; Zang et al., 2022). Similarly, in the context of vehicle durability, reliability is recognized as one of the most important determinants of consumer choice (Daziano, 2012; Train & Winston, 2007), and this extends specifically to EV adoption as well (Egbue & Long, 2012). While infrastructure reliability has not been extensively analyzed in transportation literature, it has been evaluated in other fields, such as the decision to select and remain with a mobile carrier (Keelson, 2012; Ojiaku & Osarenkhoe, 2018; Shin, 2015) and customer satisfaction with banking self-service technologies (Barua et al., 2017).

There is a very limited understanding of the effect of public charging infrastructure on the decisions to purchase or retain an EV, as determined through a previous review of both the academic literature and various market research reports (Malarkey et al., 2023). Our work determined that while many reports and studies characterize current satisfaction with public charging reliability and the factors affecting EV adoption, there is a notable gap in the data concerning the relationship between these two aspects. Using data from a 2023 Plug In America survey, we found that EV owners with at least one major concern about public charging networks were almost twice as likely to indicate that their next car would not be electric compared to those with no major concerns. This analysis, however, lacked a causal framework and was not examined in conjunction with other attributes influencing EV adoption. Additionally, the previous analysis was on current EV owners, a group that included many early adopters who are motivated by the environmental benefits of EVs and are more tolerant of challenges with charging compared with potential buyers (Plug in America, 2023). This gap motivates the current research.

2.3. Contribution of this Thesis

Among non-EV owners, there is no established understanding of the role of EV charging reliability in purchase decisions. The goal of this work is to identify how subjective perceptions of charging reliability affect EV adoption. This study makes several key contributions to the literature. First, we quantify the relationship between perceptions of public charging reliability and purchase intentions, evaluating its effect alongside other common attributes that influence EV adoption, such as price, operating cost, range, charging availability, and access to home charging. Second, our work focuses on non-EV owners. Much of the recent work in this domain has focused on understanding the impact of the charging experience for existing EV owners, but these owners tend to be tolerant of charging challenges: in the Plug in America report (2023), 84% of the sampled EV owners with multiple major concerns about charging were still likely to make their next car electric. On the other hand, it is crucial to understand these factors as they relate to potential, first-time buyers. Third, recognizing that absolute charging reliability will not always be attainable, we evaluate the impact of differing reliability perceptions on customers' willingness to buy EVs.

3. DATA

3.1. Survey Design

The data collection approach in this study was designed to explore the relationship between the perceived reliability of public charging and EV purchase decisions. To establish a causal link between perceived reliability and willingness to purchase an EV, we conducted a stated preference (SP) experiment focused on EV adoption, setting the experiment in a context where respondents were considering their next vehicle purchase. While SP experiments are limited in that they deal in hypotheticals, rather than actual behavior, they allow us to comment on causality and consider situations that may not yet exist in the comparison of different vehicles and situations.

Before the experiment, we asked respondents if they or anyone in their household owned an electric vehicle and excluded them if they answered yes. Then, we collected the socio-demographics of each respondent and either removed them based on overall representativeness of the sample or allowed them to continue.

The next part of the survey was used to collect background information relevant to respondents' purchase decisions, such as information about their household and their current primary vehicle. Respondents were asked about their perceptions of gas station reliability, to be used later in the survey and to encourage them to consider the differences between gas station reliability and public charging station reliability. Following this, the respondents were prompted to envision themselves shopping for the next vehicle they planned to purchase or lease. They were asked about their maximum budget, whether they expected to buy a new or used vehicle, and their desired vehicle class (car, SUV, pickup truck, minivan, or passenger van.) and size (small, medium, or large, depending on the class). Based on these preferences, they selected the class and general design of vehicle they wished to purchase. This information was used to personalize each respondent's choice exercises.

Since the roles of home charging and public charging are crucial to how public charging reliability may affect daily life as an EV owner, the survey introduced respondents to both types of charging and typical use cases, providing background information along with comprehension checks. Respondents were then asked if they were likely to rely on public or home charging for day-to-day use considering their own living and parking situations. Their response was shown in each of their choice exercises.

To elicit the effects of perceived reliability on EV adoption, respondents were randomly assigned to one of three reliability perception treatment groups—low, control, and high—to generate exogenous variation in perceptions of public charging reliability[1].

In the low treatment group, respondents were asked to imagine a scenario where public charging reliability was low, whereas in the high treatment group, they envisioned perfect reliability.

Specifically, the low treatment group was shown the following excerpt: "Picture a world where public charging stations are **routinely out-of-service** or **fail to operate correctly**. Charging equipment may be broken, payment systems reject drivers' credit cards, there are long lines, or for any other reason, **drivers are frequently unable to charge their vehicle** at a station. These issues **can leave EV drivers stranded** if there is no other functioning station nearby. Drivers must research not only where charging stations are, but whether they are currently working or not - and the answer may change before they arrive."

The high treatment group was shown the following: "Picture a world in which public charging stations **operate flawlessly in every respect**. Payments are seamless, equipment is in working order, and drivers can **charge successfully on the first try, every time.** This makes it convenient, even during long trips or when drivers can't charge at home. Electric vehicle drivers can charge with confidence whenever they are at a public charging station." The control group was not shown any specific information about the reliability of public chargers. This approach helped capture the potential variability in non-EV owners' perceptions of public charging reliability, which is crucial given its evolving nature and influence on EV adoption.

Following the treatment, respondents were presented with five indicator questions aimed at measuring the latent variable "perceived reliability." Given the limited coverage of perceptions of

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[1] The use of randomized perceived reliability treatments was designed based on an initial pilot study which found that non-EV owners have limited experience with public charging, lacking varied perceptions necessary for analyzing EV purchase decisions. To address potential correlation of these perceptions with other EV attitudes and eliminate endogeneity in our models (discussed further in Section 4), we used a randomized treatment approach.

public charging reliability in the literature, we adapted indicators from the fields of automation, healthcare, cellular phone service, and banking self-service. The indicators used and the questions and sources they were adapted from are shown in Table 2.

TABLE 2 Perceived reliability indicator questions and questions they were adapted from

Perceived Reliability Indicator	Original Question and Source
How would you rate the reliability of electric vehicle public chargers from 0 (worst) - 100 (best)?	"Participants were asked to rate their perceived reliability of the automation (percentage from 0 to 100)." (Barg-Walkow & Rogers, 2016)
I think electric vehicle public charging stations provide _______ service [1- Very unreliable; 2- Unreliable; 3- Somewhat unreliable; 4- Somewhat reliable; 5- Reliable; 6- Very reliable]	"I think that the smartphone provides very reliable service." (Shin, 2015)
I can depend on the service provided by electric vehicle public charging stations. [1- Strongly disagree; 2- Disagre; 3- Somewhat disagree; 4- Somewhat agree; 5- Agree; 6- Strongly agree]	"I can depend on the service provided over the bank's SST." (Barua et al., 2017)
How would you feel about electric vehicle public chargers working as they are intended to? [1- Very doubtful; 2- Doubtful; 3- Somewhat doubtful; 4- Somewhat confident; 5- Confident; 6- Very confident]	"I am worried that the mechanical system of my bank's SST will not work as I want them to." (Barua et al., 2017)
Suppose you had to depend on an electric vehicle public charger to complete an essential trip. How comfortable would you be relying on the charger? [1- Very uncomfortable; 2- Uncomfortable; 3- Somewhat uncomfortable; 4- Somewhat comfortable; 5- Comfortable; 6- Very comfortable]	"Suppose you were to received advice or information concerning everyday health matters from each of the sources. How reliable would it be?" (Worsley, 1989)

In the SP portion of the experiment, respondents completed 10 exercises where they chose between an EV and an ICEV. They were consistently reminded of the reliability conditions (as self-described through the indicator questions) both in text preceding the choice exercises and within the exercise itself.

The attributes that varied among the choice sets were price, range, operating cost, and EV charging availability, based on the review of the factors affecting EV adoption documented in Section 2. These choice tasks were generated using an optimal fractional design, calculated using Federov's exchange algorithm, which is a method to reduce the number of choice tasks from the full factorial combinations while maintaining efficiency. Our target sample size was 1,800 respondents. Therefore, we extracted 6,000 fractional factorial scenarios from the full factorial combinations, and used the same scenarios across the three treatment groups, with respondents randomly assigned to 10 choice tasks. The attributes and levels of the choice experiment are summarized in Table 3.

TABLE 3 Attribute levels used in stated preference experiment

Attribute	Mode	Level 1	Level 2	Level 3	Level 4	Level 5
Price ($)	EV	0.7 * budget	0.8 * budget	0.9 * budget	1 * budget	
	ICEV	0.7 * budget	0.8 * budget	0.9 * budget	1 * budget	
Range (miles)	EV	200	300	400		
	ICEV	200	300	400		
Car Operating Cost ($ per 100 miles)	EV	4	6	8	10	12
	ICEV	4	6	8	10	12
SUV / Truck / Van Operating Cost ($ per 100 miles)	EV	5	7.5	10	12.5	15
	ICEV	5	7.5	10	12.5	15
Public Fueling / Charging Availability (fraction of existing gas stations)	EV	0.1	0.25	0.50	0.75	1
	ICEV	1				

The attribute levels were designed to be both orthogonal and to present a scenario in which EV attributes are competitive with ICEVs in all respects, including public charging availability[2]. Additionally, purchase prices were centered around the respondents' self-reported maximum budgets to ensure that the vehicles were affordable. Respondents were also reminded of their previously selected responses, such as whether the vehicle was new or used, whether they had access to home charging, and their perceived reliability of both public charging stations and gas stations. Figure 3 illustrates one example of a choice experiment for a respondent.

[2] Current estimates for the number of public DCFC stations are equivalent to approximately 6% of existing gas stations, assuming 150,000 gas stations (NACS, 2024; U.S. Department of Energy, 2024). The lowest designed level in the experiment was 10% to reflect the expected growth in charging infrastructure from the National Electric Vehicle Infrastructure (NEVI) formula standards.

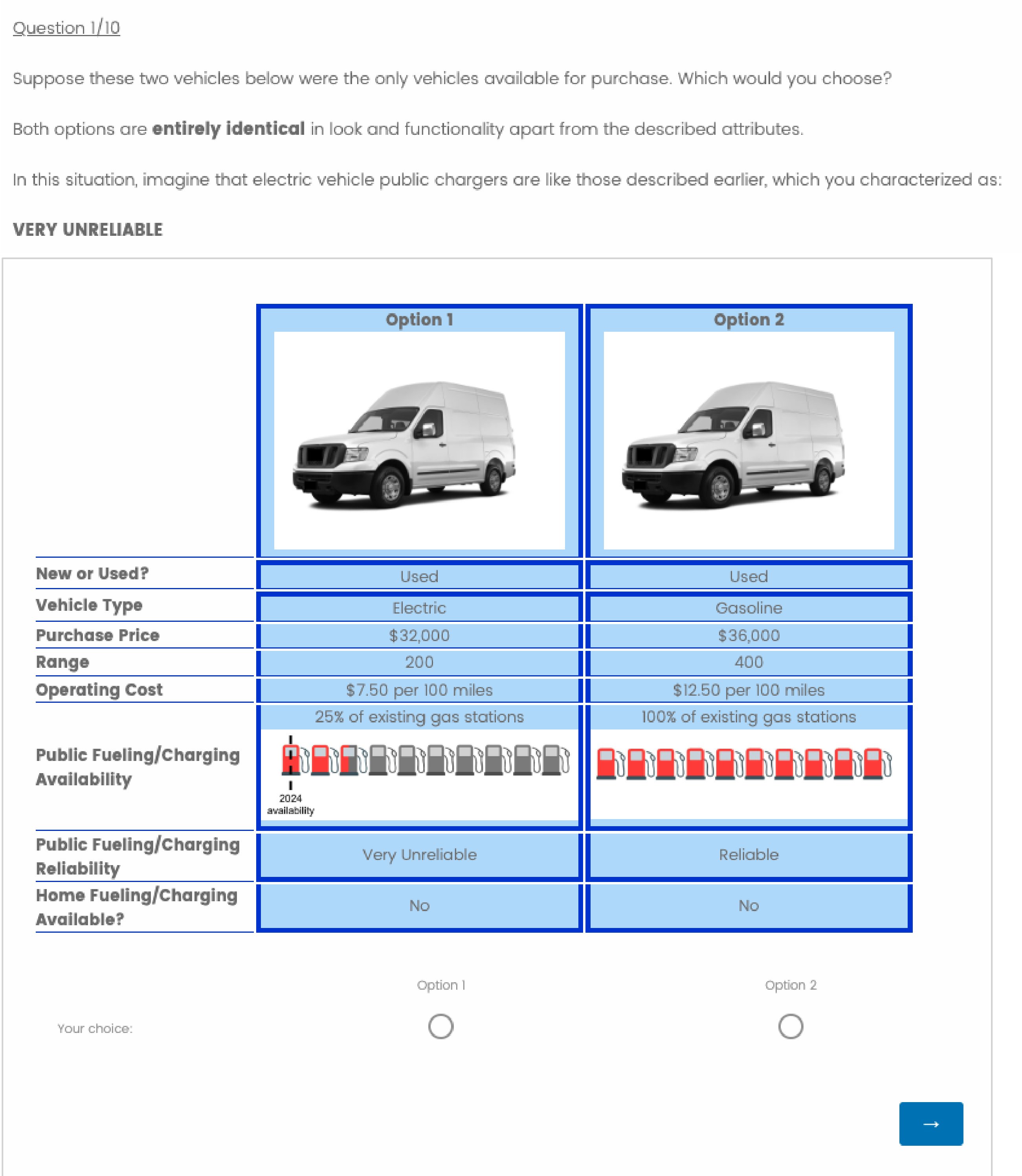


Figure 3 Sample choice experiment incorporating both experimentally designed attributes (purchase price, range, operating cost, public charging availability) and answers from respondent's previous responses (vehicle image, new or used vehicle, reliability, and home charging availability)

3.2. Summary Statistics

Our survey was conducted from March-April 2024 and distributed nationwide via Dynata, an online recruitment platform which offers benefits over other platforms for achieving representativeness (Dynata, 2024; Forsythe et al., 2023). After cleaning the data for respondents whose responses to choice exercises were not recorded properly, either due to issues in coding or how the respondent answered previous questions, the final sample size was 1,569 respondents. Table 4 shows the summary statistics of the sample.

TABLE 4 Summary statistics of sample, compared with 2020 American Community Survey

Question Statement	Categories	Respondents Before Cleaning	Respondents After Cleaning	National Population
What is your age?	Age	Median: 48	Median: 48	Median: 38.2
What is your gender?	Female	60.3%	59.9%	49.2%
	Male	39.3%	39.7%	50.8%
	Non-binary	0.4%	0.4%	-
	Not listed here	0.0%	0.0%	-
What is your race? Select all that apply.	White	53.9%	53.9%	68.6%
	Black or African American	19.3%	19.2%	13.8%
	American Indian or Alaska Native	0.4%	0.4%	1.3%
	Asian	8.3%	8.5%	6.7%
	Native Hawaiian or Other Pacific Islander	0.0%	0.0%	0.2%
	Another, or more than one	18.1%	18.0%	9.4%
What is the highest degree or level of school you have completed?	Less than bachelor’s degree	53.0%	52.8%	69.6%
	Bachelor’s degree or higher	47.0%	47.2%	30.4%

Which of the following best describes your current employment status?	Employed (Full-Time or Part-Time)	55.6%	55.5%	59.6%
	Not employed	44.4%	44.5%	40.4%
Which category best describes your household income before taxes from the last calendar year?	Under $25,000	17.5%	17.2%	18.4%
	$25,000-$49,999	23.3%	23.4%	20.6%
	$50,000-$74,999	18.8%	19.2%	17.2%
	$75,000-$99,999	14.6%	14.6%	12.8%
	$100,000-$149,999	14.2%	14.0%	15.6%
	≥ $150,000	10.1%	10.1%	15.4%
	Prefer not to answer	1.5%	1.4%	-
Do you own or rent your home?[3]	Own	55.1%	55.2%	65.2%
	Rent	40.1%	40.0%	34.8%
	Some other arrangement	4.8%	4.8%	-
What is the maximum total amount you anticipate spending on your next car purchase or lease? [4]	Used	Mean: $19,603	Mean: $19,767	Mean: $25,638
	New	Mean: $39,178	Mean: $39,290	Mean: $47,218
Treatment Group Assignment	Low Reliability Group	33.2%	33.2%	-

[3] Home ownership comparison is from 2022 (U.S. Census Bureau, 2022)

[4] Average used vehicle listing price is based on February 2024 data (Cox Automotive, 2024) and average new vehicle listing price is based on March 2024 data (Kelley Blue Book, 2024)

	High Reliability Group	34.0%	34.0%	-
	Control	32.8%	32.8%	-
Total Count		1633 Responses	1569 Responses	

69.0% of the total sample reported that they would have access to home charging. Traut et al. estimated in 2013 that 61% of U.S. households and 47% of U.S. vehicles have off-street parking at an owned residence where charging infrastructure could be installed. In our sample, 52% of respondents report having off-street parking and owning their residence. Therefore, our sample may be biased towards respondents believing in their capacity to install home charging rather than in the overall characteristics of their parking and homes.

Additionally, 54.9% of respondents chose a new car purchase and 45.1% chose a used car purchase. Of the used car buyers, 62.7% reported having access to home charging, compared to 74.4% of new car buyers. The distribution of the maximum self-reported car purchasing budgets for used car buyers is shown in Figure 4, and the distribution for new car buyers is shown in Figure 5.The minimum budget allowed was $8,000. Figures 4 and 5 illustrate a discrepancy between the maximum amount survey respondents reported being willing to pay for a vehicle and the average selling prices.

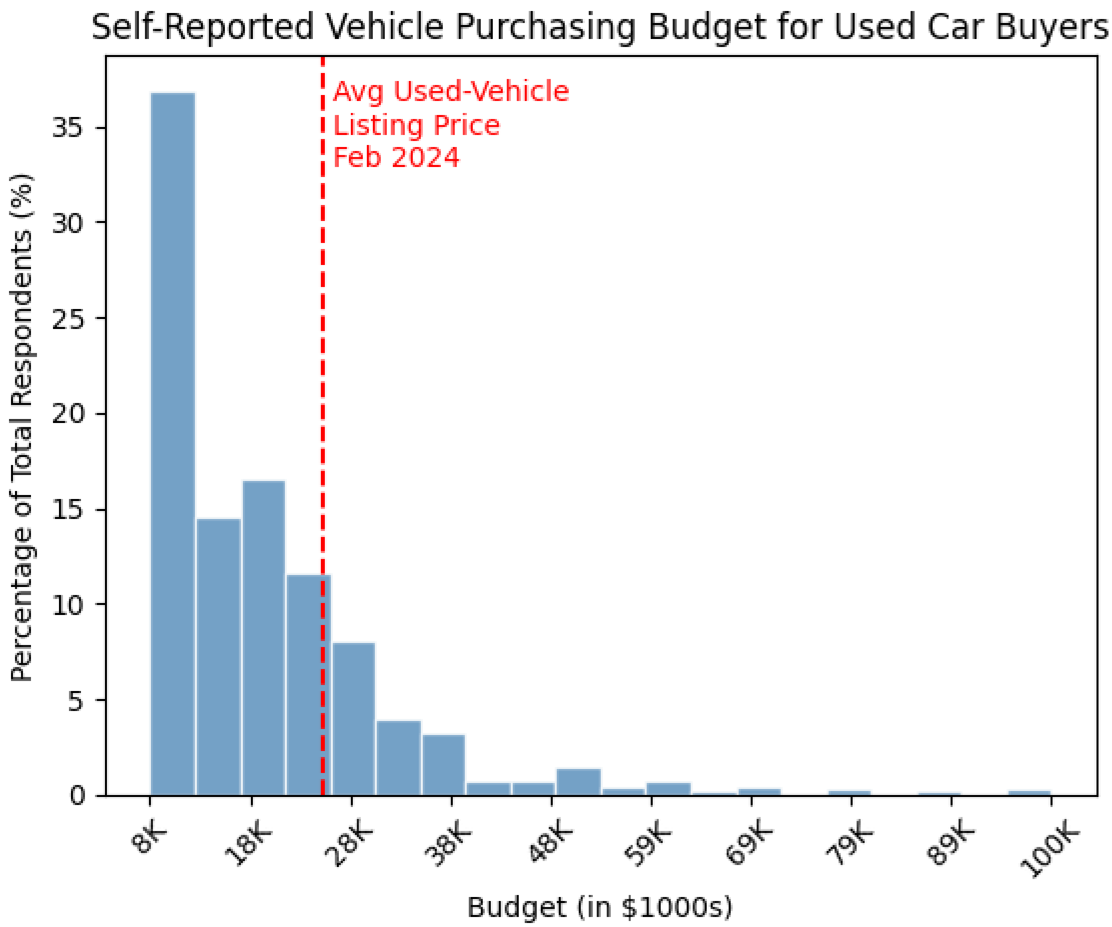


Figure 4 Self-reported maximum vehicle purchasing budget for used car buyers and comparison with 2024 average used-vehicle listing price (Cox Automotive, 2024)

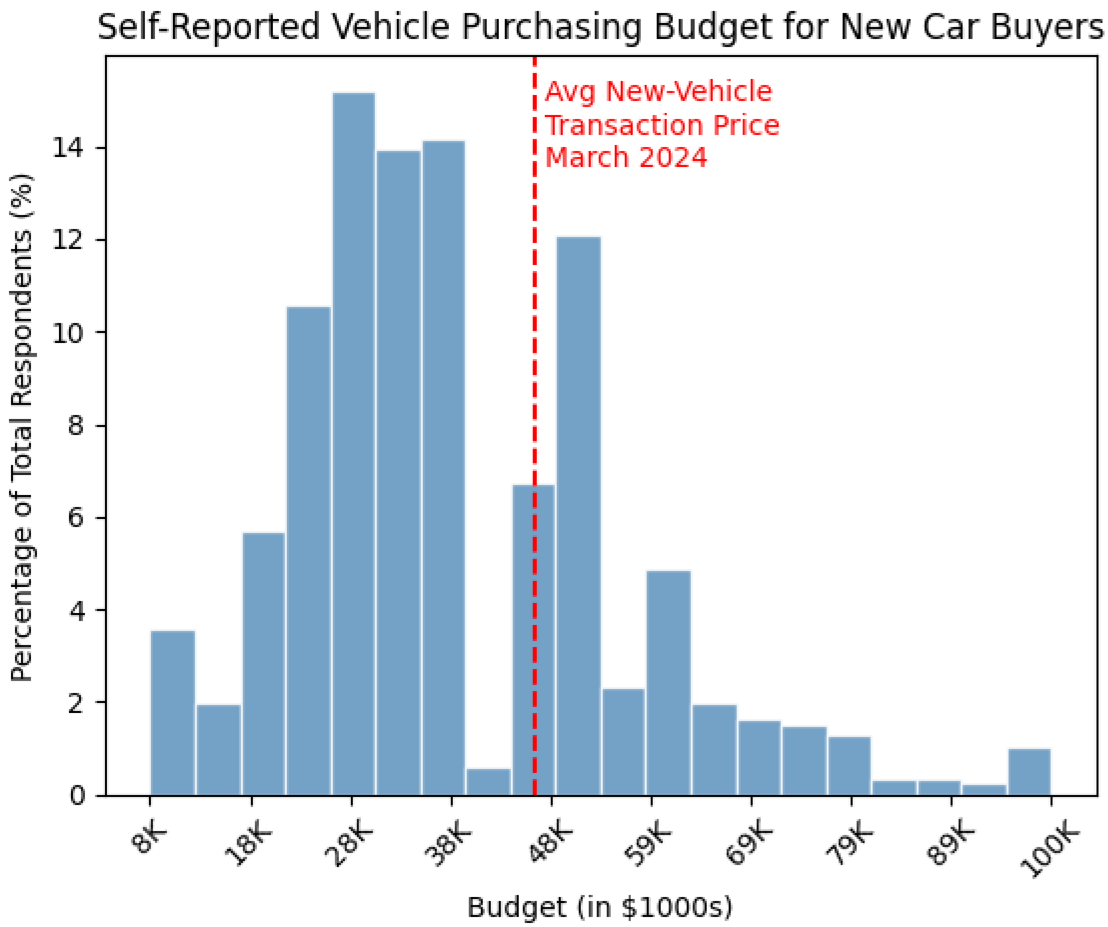


Figure 5 Self-reported maximum purchasing budget distribution for new-vehicle purchasers and comparison with average new-vehicle transaction price (Kelley Blue Book, 2024)

Figure 6 illustrates the distribution of reported gas station reliability by treatment group assignment. It indicates that perceptions of gas station reliability show similar trends across different treatment groups.

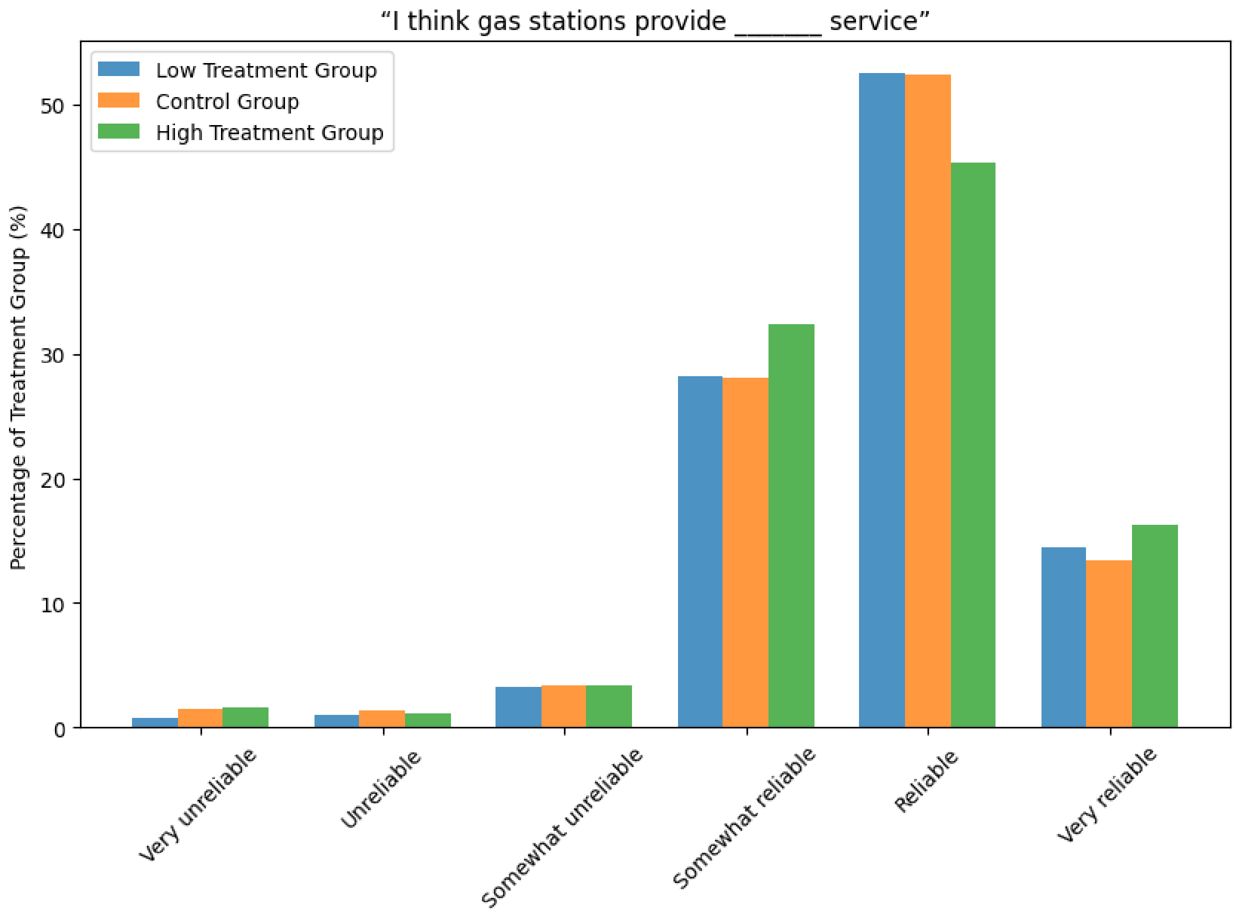


Figure 6 Self-reported gas station reliability by treatment group

4. METHODS

This study used an Integrated Choice and Latent Variable (ICLV) model to evaluate the effect of perceived charging station reliability on EV purchase decisions. ICLVs have gained popularity for modeling the effect of latent variables on choices, as they allow for the integration of observable variables as predictors of latent attributes. The observed variables are typically socio-demographic factors that underlie the attitudes, norms, and beliefs a person has (Jabbari et al., 2022; Pan et al., 2019). However, in our case, we modeled our latent variable's observable component using an instrumental variable based on the two-stage least squares (2SLS) approach to correct for endogeneity. We will briefly discuss the 2SLS framework before proceeding to the methodology used in this thesis. For more information on 2SLS, refer to Angrist & Pischke (2008).

4.1. Two-Stage Least Squares Analysis

The two stage-least squares (2SLS) approach is used in causal analyses when there is endogeneity between the causal variable of interest (hereafter referred to as the endogenous variable) and the outcome variable. To control for this endogeneity, we employ a variable (hereafter called the instrumental variable) that is exogenous to the outcome variable, meaning it is uncorrelated with any other determinants of the outcome variable, but is correlated with the endogenous variable. Methodologically, this approach is conducted in two stages: first, the endogenous variable is regressed on the instrumental variable, and second, the outcome variable is regressed on the fitted value of the endogeneous variable. The two steps are shown in Eqs. (1) and (2).

$$\alpha_i = \pi_1 z_i + \xi_{1i}, \tag{1}$$

where α_i is the endogenous variable of interest for individual i, π_1 is the coefficient of the exogenous, instrumental variable z_i, and $\xi_{1i} \sim N(0, \sigma_{1\xi})$ is the normally-distributed error term with a mean of zero and standard deviation $\sigma_{1\xi}$.

$$Y_i = \rho \widehat{\alpha}_i + \xi_{2i}, \tag{2}$$

where Y_i is the outcome variable of interest for individual i, $\widehat{\alpha}_i$ is the fitted value of the endogenous variable from the first-stage, ρ is the coefficient $\widehat{\alpha}_i$ in the causal model, and $\xi_{2i} \sim N\left(0, \sigma_{2\xi}\right)$ is the normally-distributed error term with a mean of zero and standard deviation $\sigma_{2\xi}$. For more information on the derivation of the 2SLS framework, we refer the reader to Angrist & Pischke (2008).

The variable of interest in our analysis, perceived reliability, was assumed to be endogenous with EV purchase decisions due to omitted variable bias. Unobserved factors like personal environmental values, prior exposure, or attitudes towards EVs may also affect both perceived reliability and vehicle choice. For example, a person with negative attitudes towards EVs may be less inclined to purchase one and may also consider the charging infrastructure less reliable compared to someone with more neutral attitudes towards EVs. To control for this endogeneity, we adopted the 2SLS approach and integrated it with the ICLV framework laid out in Vij & Walker (2016), since perceived reliability is also a latent variable. Our instrumental variable was the respondents' random assignment to a treatment group. Because the respondents were randomly assigned to a treatment group, the instrumental variable was uncorrelated with any of the other determinants of choice, and therefore, was not endogenous with EV purchase choices. Additionally, we assumed that group assignment affected vehicle purchasing choices only through its effect on perceived reliability, making it an appropriate instrument.

The ICLV framework has three main components, the structural model, the measurement model, and the discrete choice sub-model, and these three parts are simultaneously estimated to capture the influences of the latent endogenous variables and other explanatory variables on EV purchase choices. We integrated the 2SLS framework into the structural model to control for the endogeneity and to capture the observed part of the perceived reliability. Figure 7 provides an illustration of the model used in this study.

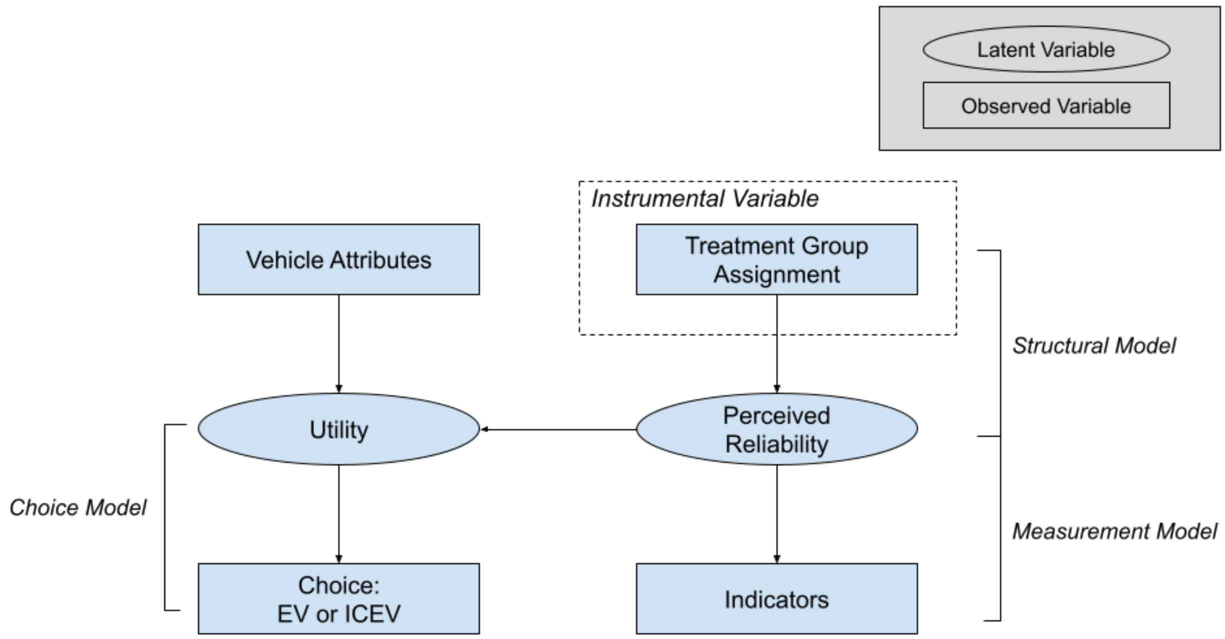


Figure 7 Modeling framework

4.2. ICLV Model

Structural Model

The structural model in is based on the first-step of the 2SLS analysis. The perceived reliability latent variable α for individual i is modeled as shown in Eq. (3).

$$\alpha_i = \gamma_0 + \gamma_l z_i + \xi_i, \quad (3)$$

where z_i is a vector of the treatment group assignment dummy instrumental variables, γ_0 is an intercept term, γ_l is a vector of parameters to be estimated, $\xi_i \sim N(0, \sigma_\xi)$ is a random disturbance term normally distributed with mean zero and standard deviation σ_ξ.

Measurement Model

There are four indicators used in the measurement model, all with 6-level ordinal responses. The probability of a given response I for individual i is estimated by the ordered probit model, as shown in Eqs. (4) and (5).

$$I_i^* = D\alpha_i + \nu_i, \sim N(0, \sigma_\nu)\ , \quad (4)$$

$$I_i = \begin{cases} 1\ if\ I_i^* < \tau_1 \\ 2\ if\ \tau_1 < I_i^* < \tau_2 \\ 3\ if\ \tau_3 < I_i^* < \tau_4\ , \\ \quad \dots \\ 6\ if\ \tau_6 > I_i^* \end{cases} \tag{5}$$

where $I_i^*$is the continuous indicator for latent variable α_i that underlies the discrete responses I_i. I_i^* is predicted by the perceived reliability latent variable α_i with coefficient D, and random disturbance term ν_i, normally distributed with mean zero and standard deviation σ_ν. I_i is the discrete probit linking respondent i's response to I_i with 6 levels, with the continuous underlying variable, based on thresholds between each response τ_6.

The probability of respondent i answering k to any given indicator question is calculated as:

$$P_i(I_i = k) = \phi\left(\frac{\tau_k - D\alpha_i}{\sigma_\nu}\right) - \phi\left(\frac{\tau_{k-1} - D\alpha_i}{\sigma_\nu}\right), \tag{6}$$

where ϕ is the cumulative distribution function of the standardized normal distribution.

Choice Model

We evaluated mode choices between EVs and ICEVs using the random utility maximization (RUM) framework. Our utility function specification is shown in Eq. (7).

$$U_{ij} = \beta_{j,x} X_{ij} + \beta_{j,\alpha}\alpha_i + ASC_j + \varepsilon_{ij}, \tag{7}$$

where U_{ij} is the utility of vehicle j for individual i, $\beta_{j,x}$ is the vector of coefficients of observed predictors, X_{ij} are the observed predictors, $\beta_{j,\alpha}$ is the coefficient of the latent variable, α_i is the latent variable perceived reliability, ASC_j is the alternative specific constant for alternative j, and ε_{ij} is the i.i.d. Gumbel distributed error term.

4.3. Distinction Between the Current Methodology and the Control-Function Method

As an aside before presenting the results of this work, we will briefly discuss the key difference between this approach and the control-function approach, which involves 2SLS and latent variable analyses, but requires more complex estimation procedures (Guevara & Ben-Akiva, 2010). The control-function approach controls for endogeneity in discrete choice models when the endogenous variable is observed. It follows the same initial step as the 2SLS approach but uses the error term from the first step as a predictor of utility in the second step, alongside the observed endogenous variable. This error term represents the latent unobserved component of the utility, and including it in the utility function addresses the omitted variable bias, thereby resolving the endogeneity issue. In our case, the endogenous variable is latent and can be predicted by its observed components through a traditional ICLV model. For more informations on the control-function approach, we refer the reader to Guevara & Ben-Akiva (2010) and Train (2009).

5. MODEL RESULTS

We first conducted an exploratory factor analysis to examine the relationship between the indicator questions and the perceived reliability latent variable. The scree plot shown in Figure 8 indicated one latent variable underlied the data, as designed. The results of the factor analysis are shown in Table 5. One latent variable and five indicator questions explained 80% of the total variance.

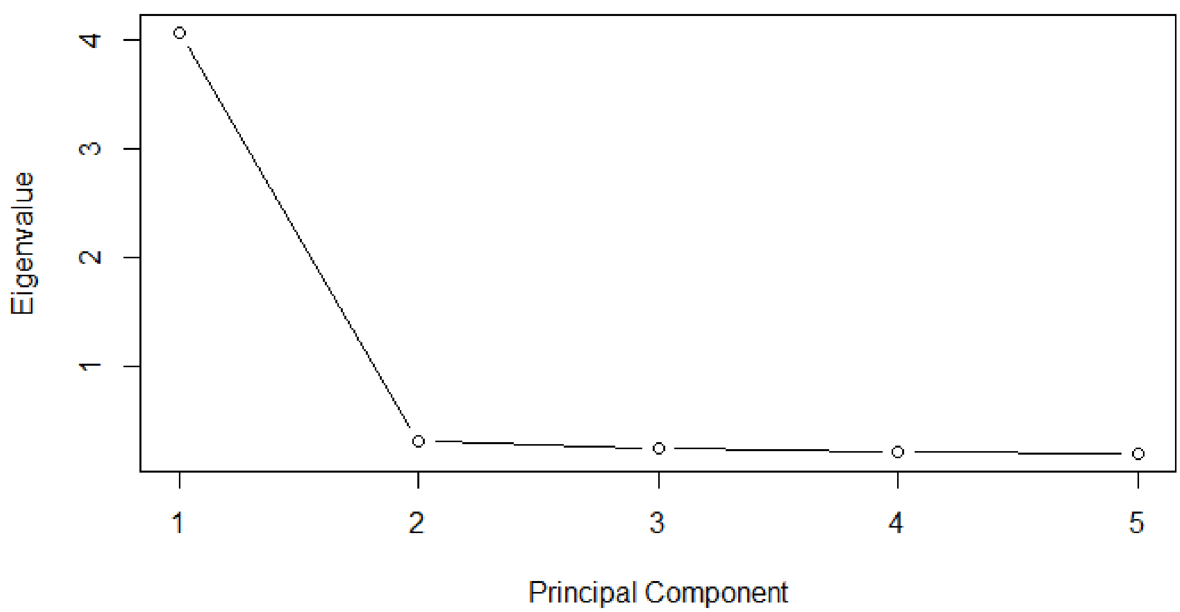


Figure 8 Scree plot of reliability indicators

TABLE 5 Results from exploratory factor analysis of indicator questions and perceived reliability factor

Indicator Question	Loading
How would you rate the reliability of electric vehicle public chargers from 0 (worst) - 100 (best)?	0.862
I think electric vehicle public charging stations provide _______ service [1- Very unreliable; 2- Unreliable; 3- Somewhat unreliable; 4- Somewhat reliable; 5- Reliable; 6- Very reliable]	0.877

I can depend on the service provided by electric vehicle public charging stations. [1- Strongly disagree; 2- Disagre; 3- Somewhat disagree; 4- Somewhat agree; 5- Agree; 6- Strongly agree]	0.898
How would you feel about electric vehicle public chargers working as they are intended to? [1- Very doubtful; 2- Doubtful; 3- Somewhat doubtful; 4- Somewhat confident; 5- Confident; 6- Very confident]	0.902
Suppose you had to depend on an electric vehicle public charger to complete an essential trip. How comfortable would you be relying on the charger? [1- Very uncomfortable; 2- Uncomfortable; 3- Somewhat uncomfortable; 4- Somewhat comfortable; 5- Comfortable; 6- Very comfortable]	0.845

We used the factor scores extracted from the exploratory factor analysis to visualize the differences in perceived reliability across treatment groups, as illustrated in Figures 9 through 11. This highlights that the control group exhibits a more favorable perception of public charging reliability than the low treatment group, but a less favorable perception than the high treatment group.

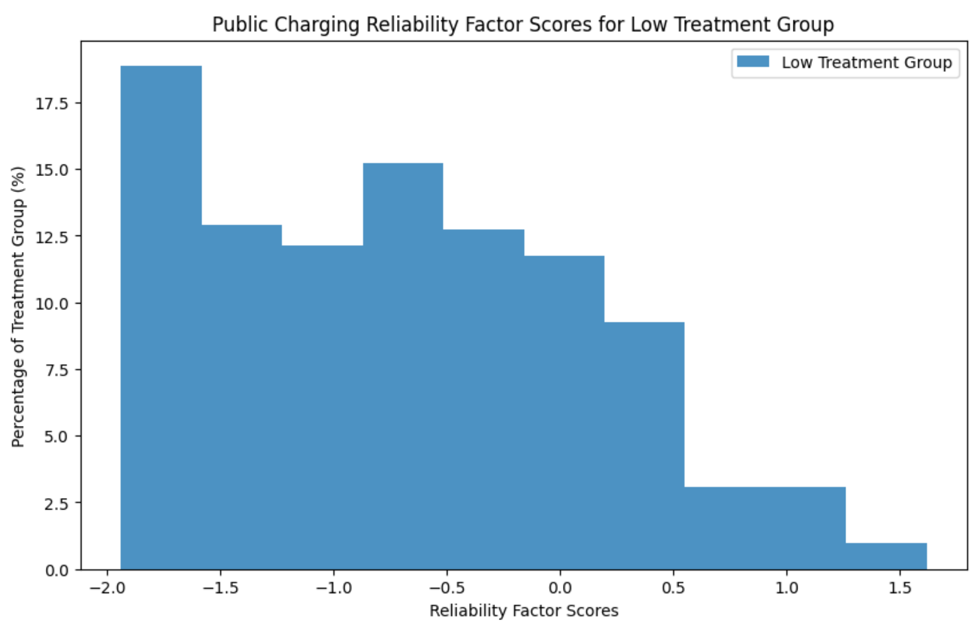


Figure 9 Public charging reliability factor scores for low reliability treatment group

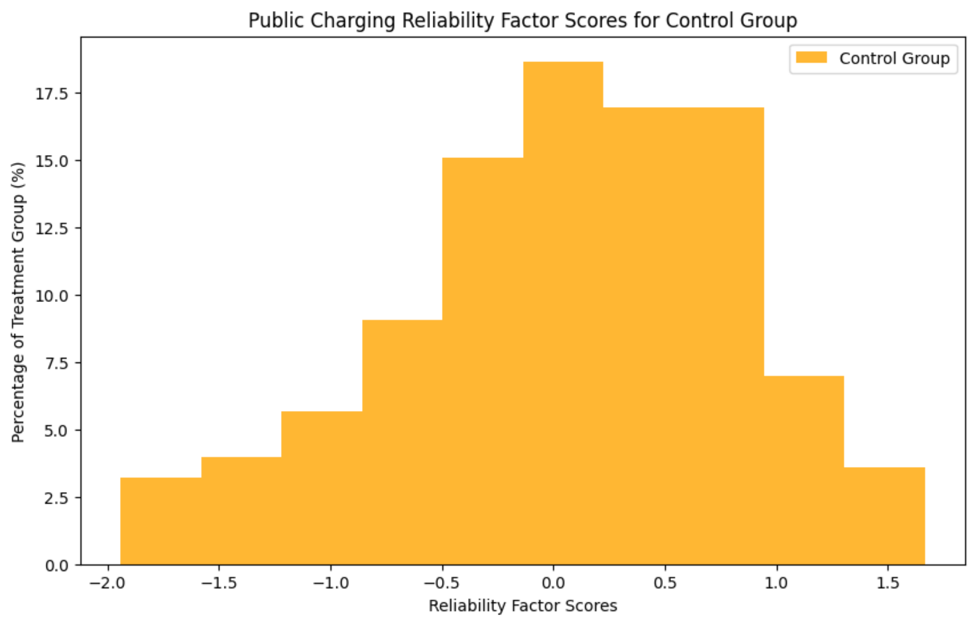


Figure 10 Public charging reliability factor scores for control group

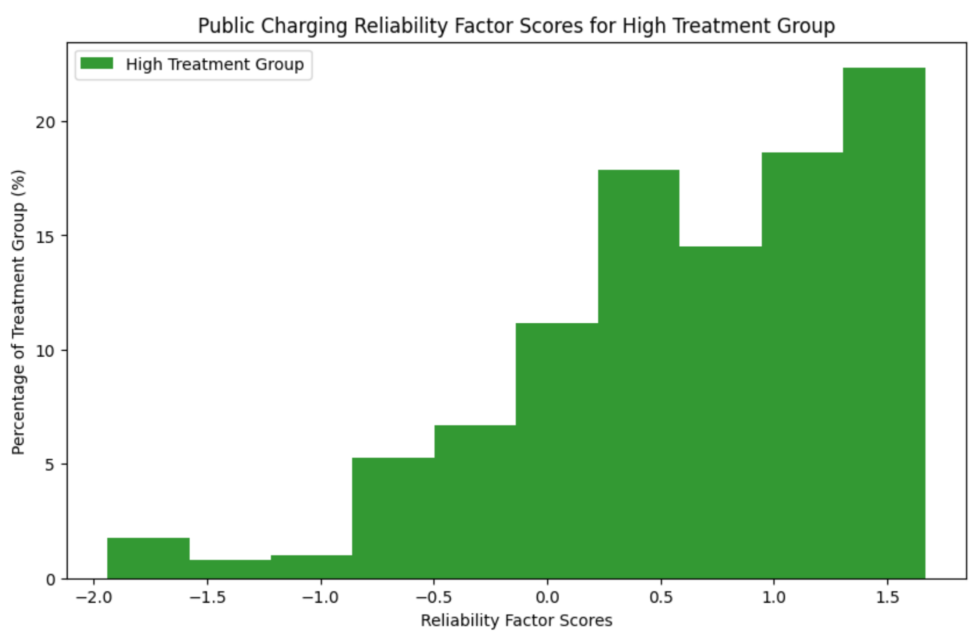


Figure 11 Public charging reliability factor scores for high reliability treatment group

We also used the factor scores to conduct a traditional 2SLS using the factor scores as the endogenous variable and the choice as the direct outcome. This analysis confirmed the strength of the instrument, but as it is not of primary interest in this paper, is not discussed further here. The full results are available in Appendix B.

After confirming the strength of the instrument through the factor analysis and a regression on the factor scores, we estimated the ICLV model using the Python Biogeme package (version 3.2.13). The final model specification was developed as a binary logit. Different functional forms were tested for the range variable in the choice model, including a linear form, a logarithmic form, and a quadratic form, but a linear relationship provided the best fit. The full model results are shown in Table 6.

The structural model indicates the treatment group assignment served as a strong instrument for perceived reliability, as seen by the statistical significance of the treatment group dummy variables. The difference between the control group (as seen from the intercept term) and the low treatment group is 0.82 and the difference between the control group and the high treatment group is 0.511. This indicates that when no particular information was provided, respondents in the control group reported reliability perceptions closer to those of the high treatment group than to those of the low treatment group. Additionally, the standard deviation of the error term of the structural model is large, indicating there are many other unobserved factors that affect perceived reliability, justifying the use of the 2SLS approach. The measurement model shows a strong relationship between the indicators and the latent variable. While five indicators were designed for the perceived reliability latent variable, one ("How would you rate the reliability of electric vehicle public chargers from 0 (worst) - 100 (best)?") caused the likelihood to be close to zero, invoking an issue with generating the log, and resulting in zero standard errors. Therefore, we removed this indicator from the model. The remaining four were used in the final model specification, with Indicator 2 serving as the reference.

In the choice model, the propensity to choose EVs decreased as their prices and operating costs increased. The effects of price and operating cost were statistically significant for both EV and ICEV choices but were not statistically different from each other. In other words, these factors played an equal role in the utility of EVs and ICEVs, respectively, indicating that respondents viewed the two cars as comparable in the value of price, range, and operating cost. The effect of range was statistically significant for both EV and ICEV choices, but an additional 100 miles of range for an EV provided a greater change in utility than that of an ICEV. This is consistent with prior literature findings that EV range plays an important role in consumer purchase decisions, and has a higher marginal utility than ICEV driving range (Jensen et al., 2013). Additionally, the ASC values still indicate that EVs have a lower base utility than conventional vehicles, indicating hesitation from potential buyers. This holds true both for people who have access to home charging and people who have to rely on public charging. However, the ASCs across these two groups are not statistically different, indicating close alignment in the evaluation of EVs' base utility between these groups.

The effects of the availability and reliability of public EV charging infrastructure were positive and statistically significant, indicating that as respondents perceive increased availability and reliability of public charging, they are more likely to choose EVs. Comparing these results across respondents with access to home charging and those without yields interesting findings. The effect of public EV charging availability and reliability was the same regardless of whether people had access to home charging. This result is counterintuitive, as residents without home charging are more dependent on public charging for day-to-day use. Instead, it suggests that the availability and reliability of public charging are important to all buyers, regardless of expected usage. This aligns with White et al.'s (2022) finding that the presence of public chargers makes potential buyers more receptive to purchasing EVs, not due to concerns about mobility restrictions, but because more chargers make EVs more visible, and therefore, more socially preferable.

TABLE 6 ICLV model results

Variable	Value	Std. Error
CHOICE MODEL		
EV Intercept	-0.763	0.272
ICEV Operating Cost ($/100 miles)	-0.076	0.007
EV Operating Cost ($/100 miles)	-0.091	0.007
ICEV Price (Multiplier: Price Shown / Budget)	-2.470	0.224
EV Price (Multiplier: Price Shown / Budget)	-3.000	0.229
ICEV Range (hundreds of miles)	0.160	0.029
EV Range (hundreds of miles)	0.266	0.029
Public Charging Availability (log fraction of existing gas stations)	0.637	0.0372
Charging Station Perceived Reliability Respondents w/ Home Charging	0.850	0.148
Charging Station Perceived Reliability Respondents w/o Home Charging	0.737	0.123
STRUCTURAL MODEL		
Intercept	0.454	0.076
High reliability treatment assignment (dummy)	0.858	0.134
Low reliability treatment assignment (dummy)	-1.320	0.154
S.d. for error term	1.530	0.113
MEASUREMENT MODEL		
Coefficient for I2	1.010	0.022
Coefficient for I3	0.942	0.020
Coefficient for I4	1.040	0.028
Intercept for I2	-0.040	0.035
Intercept for I3	-0.116	0.034
Intercept for I4	-0.340	0.050
S.d. for I2	0.902	0.055

S.d. for I3	0.861	0.045
S.d. for I4	1.080	0.069
Difference between thresholds 1,2 & 4,5	1.270	0.078
Difference between thresholds 2,3 & 5,6	1.120	0.074
I1: "I think electric vehicle public charging stations provide ____ service" (Reference) *I2: "I can depend on the service provided by electric vehicle public charging stations"* *I3: "How would you feel about electric vehicle public chargers working as they are intended to?"* *I4: "Suppose you had to depend on an electric vehicle public charger to complete an essential trip. How comfortable would you be relying on the charger?"*		
Sample Size | Observations | AIC | BIC	1569 | 15690 | 31421 | 31555	

Based on the model results, we calculated the equivalent changes in various vehicle and infrastructure attributes—such as price, operating cost, range, and charging availability—corresponding to the difference in average perceived reliability between the control group and the low reliability treatment group. First, we calculated the change in utility for the difference in the perceived reliability, α, as shown in Eq. (8).

$$\Delta U_{\Delta\alpha} = \beta_{\alpha,home\ charging} \times \Delta\alpha, \quad (8)$$

where $\Delta U_{\Delta\alpha}$ is the change in utility associated with a $\Delta\alpha$ change in perceived reliability between the control group and the low reliability treatment group. $\beta_{\alpha,home\ charging}$ is the the estimated coefficient of perceived reliability for respondents with home charging. The equation with the values from Table 6 is shown in Eq. (9).

$$\Delta U_{\Delta\alpha} = 0.737 \times -1.32 = -0.973 \quad (9)$$

Then, we calculate the equivalent values for attribute X with coefficient β_X as follows:

$$\Delta X = \frac{\Delta U_{\Delta\alpha}}{\beta_X} \quad (10)$$

Table 7 shows the results of the equivalent coefficient values for the 1.32-unit decrease in perceived reliability, corresponding to the difference between the control group and the low reliability treatment group.

TABLE 7 Change in vehicle and infrastructure attributes equivalent to the change in utility generated by a 1.32 unit reduction in perceived reliability

Variable	Equivalent Change in Attributes
EV Price on a $50,000 budget	+ 32% increase on purchase price
EV Range	- $3.86/gallon

EV Charging Stations[5]	- 32,571 stations
Price of Gas for a Vehicle with 30 mpg Fuel Efficiency	- 366 miles of range

Table 7 highlights the effect of a difference in perceived reliability on the utility of EVs. The difference in perceived reliability for each indicator between the control group and the low reliability treatment group (a difference of 1.32 units) is shown in Figures 12 through 15. These figures illustrate that there is still variation in perceptions of reliability for both groups. However, the low reliability treatment group perceives reliability as poorer overall compared to the control group.

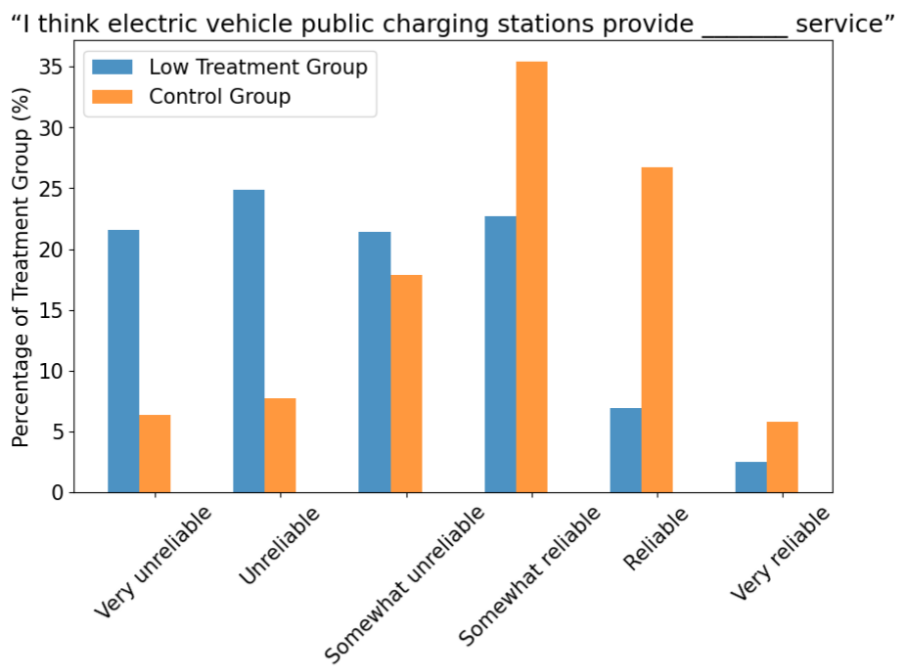


Figure 12 Difference in the distribution of responses for perceived reliability indicator 2 between control group and low reliability treatment group

[5] This number is again based on recent estimates that there are approximately 150,000 gas stations in the United States (NACS, 2024).

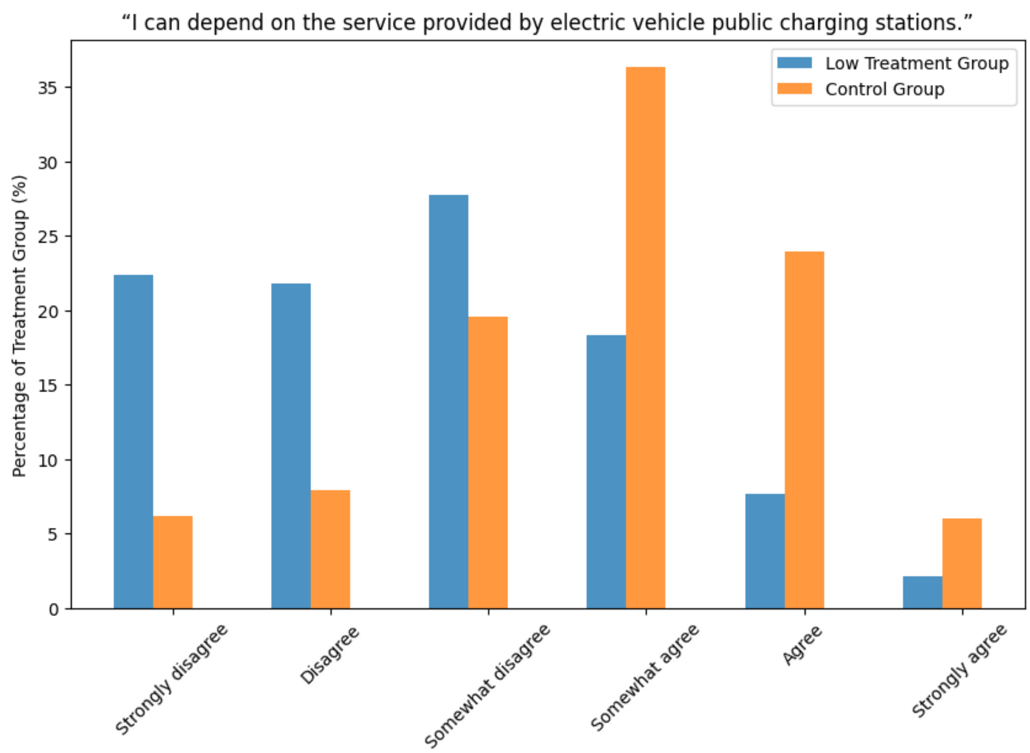


Figure 13 Difference in the distribution of responses for perceived reliability indicator 3 between control group and low reliability treatment group

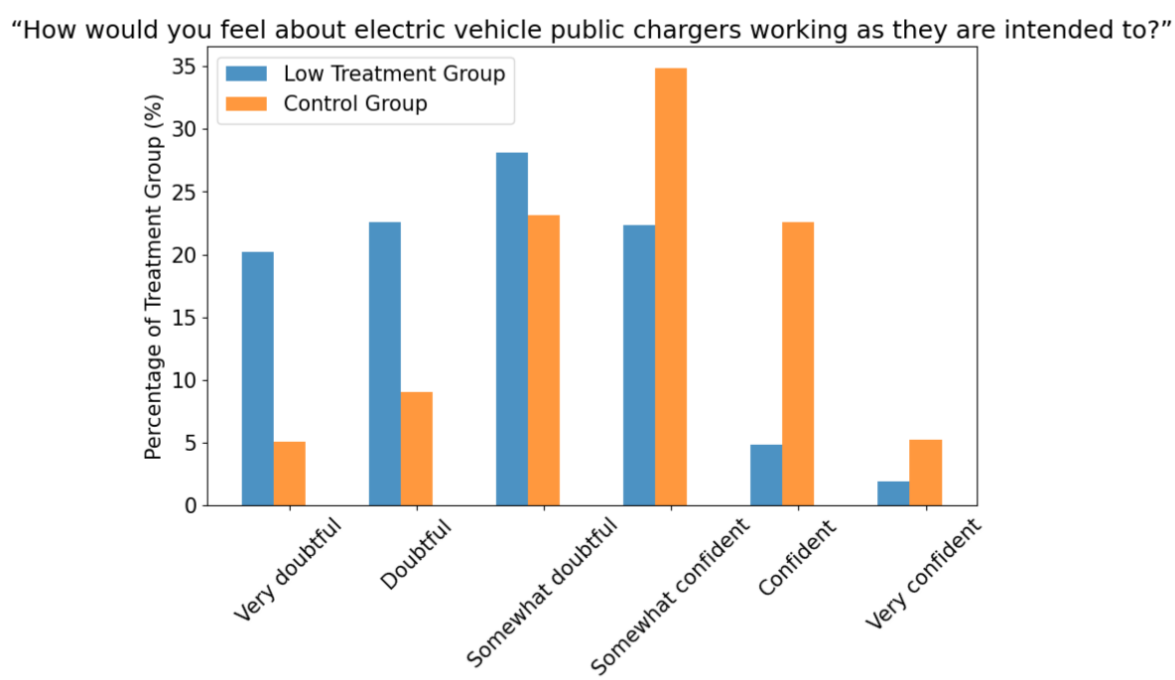


Figure 14 Difference in the distribution of responses for perceived reliability indicator 4 between control group and low reliability treatment group

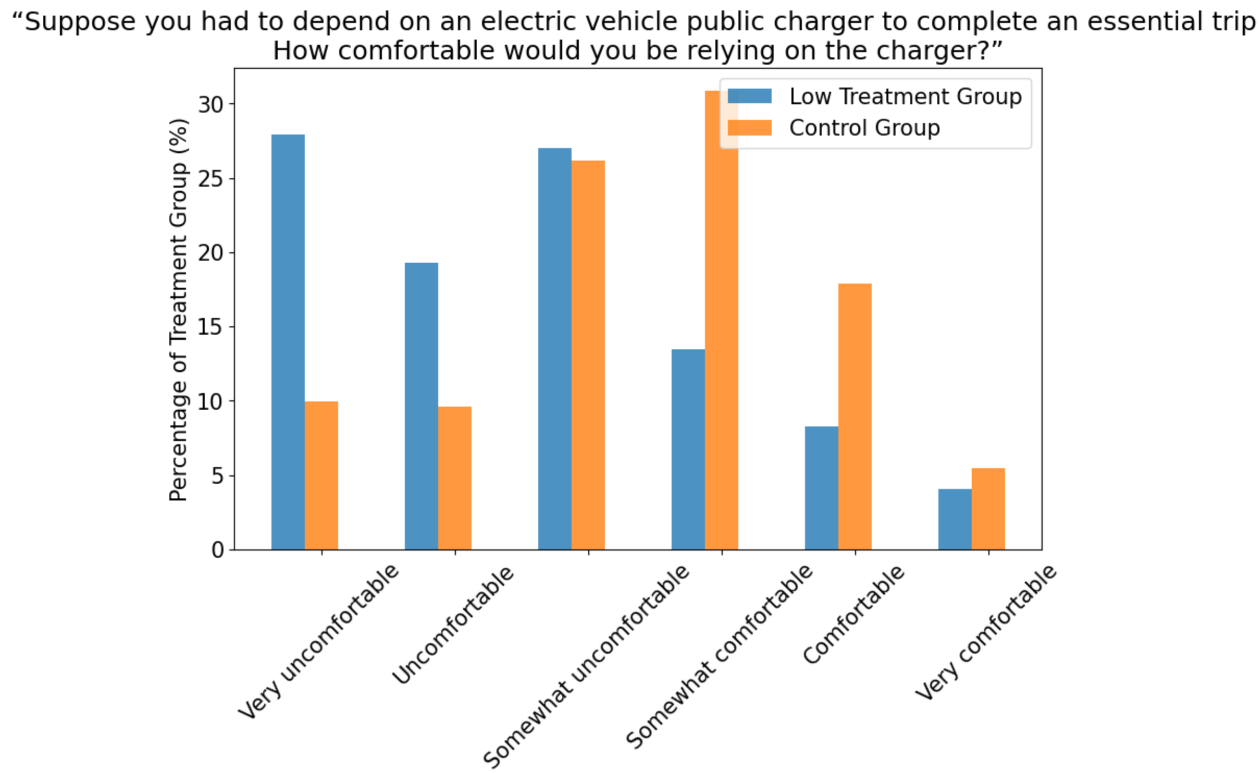


Figure 15 Difference in the distribution of responses for perceived reliability indicator 5 between control group and low reliability treatment group

Although perceived reliability itself has not been extensively studied, the effect of the other attributes—price, range, operating cost and infrastructure—has been well-documented, and are known to play a crucial role in the adoption of electric vehicles (Liao et al., 2017). The difference in purchase price on a $50,000 vehicle larger than the $7,500 federal tax credit for new EVs (IRS, 2024). The range difference is close to the average new EV's range (Randall, 2023). Additionally, the reduction of 32,571 public charging stations is significant, given that there are currently around 13,000 fast charging stations in the U.S. (U.S. Department of Energy, 2024). These values highlight the importance of addressing perceived reliability issues to facilitate the transition to electric vehicles.

6. DISCUSSION AND CONCLUSION

Consumer preferences for EVs are shaped by many factors, with charging infrastructure playing a significant role. In this paper, we used a stated preference choice experiment and an integrated modeling approach to examine the role of perceived reliability on EV adoption for potential buyers. While the role of charging station availability has been extensively studied in the literature, the impact of poor reliability has received little to no attention but is becoming an increasing concern for policymakers. By estimating the magnitude of this effect, we highlight the value and importance of investments to improve public charging reliability.

Our analysis demonstrated the critical influence of public charging station reliability on willingness to adopt an EV. After assigning respondents to randomized reliability treatment groups, we examined the difference in perceptions of reliability between the “control group” and the “low reliability group”. The public chargers described to the low reliability treatment group closely mimicked the current state of EV public chargers – unreliable, with failing payment systems, and frequently leaving drivers stranded. The control group was not given any prior information about the state of public chargers and reported higher perceptions of reliability compared to the low reliability group. The change in utility corresponding to the difference between the two groups showed significant implications for EV market growth. As potential buyers become more aware of the poor reliability conditions that currently exist, we can expect a significant decrease in EV market shares. This awareness could deter buyers who are otherwise inclined towards EVs due to environmental benefits or cost savings.

It is also crucial to note that the negative effect of public charging reliability in our analysis was consistent across individuals with access to home charging and those without. This suggests that even if people do not expect to use public chargers on a regular basis, having access to a reliable charger when needed remains critical in purchase decisions. Furthermore, since public chargers are essential to completing long distance trips, addressing these concerns is essential for sustaining consumer confidence during such trips, which have a greater environmental impact than shorter trips.

Additionally, while our analysis considered individuals’ own perceptions, this is only one piece of the decision-making process, as outlined by the Theory of Planned Behavior (Ajzen, 1991). As people’s families and friends begin to have more negative experiences with public charging, this will influence social norms, directly impacting the decision-making process and further amplifying the effect of poor perceptions of reliability. If public charging concerns remain unaddressed, it could lead to missed opportunities in reducing carbon emissions and promoting cleaner transportation alternatives.

On the other hand, if reliability perceptions were to improve, this would significantly improve potential buyers’ willingness to purchase an EV. Our results indicate that improving reliability from the low reliability group to the control group is equivalent to increasing the number of public charging stations by over 200%, based on the current estimates of DCFC stations in the U.S (U.S. Department of Energy, 2024). Therefore, investments should not merely focus on increasing the number of public charging stations but also prioritize enhancing their reliability. There are promising developments in improving reliability nationwide. For example, The Tesla network, which has better public charging satisfaction among its customers (Malarkey et al., 2023), will soon be accessible to many other vehicle providers (Barry & Bartlett, 2024)..This could significantly improve perceptions of public charging reliability and make EVs more appealing to consumers. Additionally, the recent $100 million investment in enhancing charging infrastructure reliability and the establishment of the National Charging Experience Consortium represent concerted efforts to address EV charging challenges (Malarkey et al., 2023).

This research opens several avenues for future work. For one, it is essential to explore how different market segments perceive charging reliability and how these perceptions influence their specific adoption rates. Future studies should determine the factors necessary for the most resistant consumers to accept EVs and assess the extent to which any negative experiences with charging infrastructure impacts their willingness to adopt. While this study does not evaluate how a failed experience maps onto reliability perceptions, future work could explore this avenue to gain an understanding of what threshold of reliability is acceptable to consumers. Longitudinal studies could also assess how investments in public charging reliability influence consumer attitudes and market dynamics over time.

In conclusion, this study provides compelling evidence that public charging station reliability is a linchpin in the adoption of electric vehicles. Ensuring the reliability of these stations is as critical as expanding their network, and both aspects should be pursued concurrently to achieve the desired increase in EV uptake and the broader environmental benefits associated with reduced vehicular emissions.

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alanazi, F. (2023). Electric Vehicles: Benefits, Challenges, and Potential Solutions for Widespread Adaptation. *Applied Sciences*, *13*(10), Article 10. https://doi.org/10.3390/app13106016

Alexander, B., Marotta Jr., F., Doran, T., & Galati, L. (2023). *Electric Vehicle Infrastructure: Public Charging Reliability, Definitions, & Calculations*. General Motors.

Angrist, J., & Pischke, J.-S. (2008). IV and Causality. In *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Barg-Walkow, L. H., & Rogers, W. A. (2016). The Effect of Incorrect Reliability Information on Expectations, Perceptions, and Use of Automation. *The Journal of Human Factors and Ergonomics Society*, *58*(2), 242–260.

Barry, K., & Bartlett, J. S. (2024, May 14). Automakers Move to a Common Plug Standard to Allow Their EVs to Use Tesla Superchargers. *Consumer Reports*. https://www.consumerreports.org/cars/hybrids-evs/tesla-superchargers-open-to-other-evs-what-to-know-a9262067544/

Barua, Z., Aimin, W., & Hongyi, X. (2017). A perceived reliability-based customer satisfaction model in self-service technology. *The Service Industries Journal*, *38*(7–8), 446–466. https://doi.org/10.1080/02642069.2017.1400533

Bockarjova, M., Rietveld, P., Knockaert, J., & Steg, L. (2014). *Dynamic Consumer Heterogeneity in Electric Vehicle Adoption* (14–1579). Article 14–1579. Transportation Research Board 93rd Annual MeetingTransportation Research Board. https://trid.trb.org/View/1287882

CARB. (2024). *States that have Adopted California's Vehicle Regulations*. California Air Resources Board. https://public.tableau.com/views/Section177StatesandRegulationCodes_16986822692920/Section177StatesRulesGradient?:embed=y&:showVizHome=no&:host_url=https%3A%2F%2Fpublic.tableau.com%2F&:embed_code_version=3&:tabs=no&:toolbar=yes&:animate_transition=yes&:display_static_image=no&:display_spinner=no&:display_overlay=yes&:display_count=yes&:language=en-US&publish=yes&:loadOrderID=0

Carrion, & Levinson. (2012). Value of travel time reliability: A review of current evidence—ScienceDirect. *Transportation Research Part A: Policy and Practice*, *46*(4), 720–741.

Chorus, C. G., & Kroesen, M. (2014). On the (im-)possibility of deriving transport policy implications from hybrid choice models. *Transport Policy*, *36*, 217–222. https://doi.org/10.1016/j.tranpol.2014.09.001.

Consumer Reports. (2022a). *Battery Electric Vehicles and Low Carbon Fuel: A Nationally Representative Multi-Mode Survey*. https://article.images.consumerreports.org/prod/content/dam/surveys/Consumer_Reports_BEV%20AND%20LCF%20SURVEY_18_FEBRUARY_2022

Consumer Reports. (2022b). *Electric Vehicle Owners: A Nationally Representative Multi-Mode Survey*. https://article.images.consumerreports.org/image/upload/v1679253682/prod/content/dam/surveys/Consumer_Reports_EV_Owners_October_November_2022.pdf

Cox Automotive. (2023). *Path to EV Adoption: Consumer and Dealer Perspectives*.

Cox Automotive. (2024, February 16). Used-Vehicle Supply and Average Listing Price Declined in January. *Cox Automotive Inc.* https://www.coxautoinc.com/market-insights/used-vehicle-inventory-january-2024/

Daziano, R. A. (2012). Taking account of the role of safety on vehicle choice using a new generation of discrete choice models. *Safety Science*, *50*(1), 103–112. https://doi.org/10.1016/j.ssci.2011.07.007

Dvorak, P. (2023). The Valley of Fire is no place to be when your EV is out of power. *The Washington Post*. https://www.washingtonpost.com/dc-md-va/2023/07/31/electric-vehicle-anxiety-logistics/

Dynata. (2024). *Dynata Global Panel Book*. https://www.dynata.com/market-researcher-solutions/global-audiences/

Egbue, O., & Long, S. (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy*, *48*, 717–729. https://doi.org/10.1016/j.enpol.2012.06.009

Egnér, F., & Trosvik, L. (2018). Electric vehicle adoption in Sweden and the impact of local policy instruments. *Energy Policy*, *121*, 584–596. https://doi.org/10.1016/j.enpol.2018.06.040

Fabianek, P., & Madlener, R. (2023). Multi-Criteria assessment of the user experience at E-Vehicle charging stations in Germany. *Transportation Research Part D: Transport and Environment*, *121*, 103782. https://doi.org/10.1016/j.trd.2023.103782

Forsythe, C. R., Gillingham, K. T., Michalek, J. J., & Whitefoot, K. S. (2023). Technology advancement is driving electric vehicle adoption. *Proceedings of the National Academy of Sciences*, *120*(23), e2219396120. https://doi.org/10.1073/pnas.2219396120

Franke, T., & Krems, J. F. (2013). Understanding charging behaviour of electric vehicle users. *Transportation Research Part F: Traffic Psychology and Behaviour*, *21*, 75–89. https://doi.org/10.1016/j.trf.2013.09.002

Guevara, C. A., & Ben-Akiva, M. (2010). Addressing Endogeneity in Discrete Choice Models: Assessing Control-Function and Latent-Variable Methods. In S. Hess & A. Daly (Eds.), *Choice Modelling: The State-of-the-art and The State-of-practice* (pp. 353–370). Emerald Group Publishing Limited. https://doi.org/10.1108/9781849507738-016

Hackbarth, A., & Madlener, R. (2013). Consumer preferences for alternative fuel vehicles: A discrete choice analysis. *Transportation Research Part D: Transport and Environment*, *25*, 5–17. https://doi.org/10.1016/j.trd.2013.07.002

Helveston, J. P., Liu, Y., Feit, E. M., Fuchs, E., Klampfl, E., & Michalek, J. J. (2015). Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China. *Transportation Research Part A: Policy and Practice*, *73*, 96–112. https://doi.org/10.1016/j.tra.2015.01.002

Hoen, A., & Koetse, M. J. (2014). A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. *Transportation Research Part A: Policy and Practice*, *61*, 199–215. https://doi.org/10.1016/j.tra.2014.01.008

Huang, Y., Qian, L., Tyfield, D., & Soopramanien, D. (2021). On the heterogeneity in consumer preferences for electric vehicles across generations and cities in China. *Technological Forecasting and Social Change*, *167*, 120687. https://doi.org/10.1016/j.techfore.2021.120687

IRS. (2024, May 14). *Credits for new clean vehicles purchased in 2023 or after | Internal Revenue Service*. https://www.irs.gov/credits-deductions/credits-for-new-clean-vehicles-purchased-in-2023-or-after

Jabbari, P., Auld, J., & MacKenzie, D. (2022). How do perceptions of safety and car ownership importance affect autonomous vehicle adoption? *Travel Behaviour and Society*, *28*, 128–140.

Jackson, C., Berg, J., & Wiseman, T. (2023, October 11). Majority of Americans say they are unlikely to purchase electric vehicles | Ipsos. *Ipsos*. https://www.ipsos.com/en-us/majority-americans-say-they-are-unlikely-purchase-electric-vehicles

J.D. Power. (2022, August 17). *Growing Electric Vehicle Market Threatens to Short-Circuit Public Charging Experience, J.D. Power Finds*. https://www.jdpower.com/business/press-releases/2022-us-electric-vehicle-experience-evx-public-charging-study

J.D. Power. (2023). *Public Charging Issues May Short-Circuit EV Growth*. https://www.jdpower.com/business/press-releases/2023-us-electric-vehicle-experience-evx-public-charging-study

Jenn, A., Springel, K., & Gopal, A. R. (2018). Effectiveness of electric vehicle incentives in the United States. *Energy Policy*, *119*, 349–356.

Jensen, A. F., Cherchi, E., & Mabit, S. L. (2013). On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transportation Research Part D: Transport and Environment*, *25*, 24–32. https://doi.org/10.1016/j.trd.2013.07.006

Joint Office of Energy and Transportation. (2023, September 13). *Biden-Harris Administration to Invest $100 Million for EV Charger Reliability · Joint Office of Energy and Transportation*. https://driveelectric.gov/news/ev-reliability-funding-opportunity

Karanam, V., & Tal, G. (2023). *How Disruptive are Unreliable Electric Vehicle Chargers? Empirically Evaluating the Impact of Charger Reliability on Driver Experience*. https://doi.org/10.21203/rs.3.rs-2592351/v1

Keelson, S. A. (2012). *Factors Affecting Consumer Choice of Multiple Mobile Services* (SSRN Scholarly Paper 2145648). https://papers.ssrn.com/abstract=2145648

Kelley Blue Book. (2024, April 15). *New-Vehicle Average Transaction Prices Drop to Lowest Level in nearly Two Years, According to Latest Kelley Blue Book Estimates*. Kelley Blue Book | MediaRoom. https://mediaroom.kbb.com/2024-04-15-New-Vehicle-Average-Transaction-Prices-Drop-to-Lowest-Level-in-nearly-Two-Years,-According-to-Latest-Kelley-Blue-Book-Estimates

Kurani, K., & Ogunmayin, J. M. (2023). *How Electric Vehicle Drivers Navigate the Real and Virtual Worlds of Vehicle Charging*. EVS36 Symposium, Sacramento, CA.

Li, C., Zhang, S., Ling, W., Zhao, L., & Pan, Y. (2024). Enhancing User Experience in Electric Vehicle Charging Applications (EVCA): A Comprehensive Analysis in the Chinese

Context. *Journal of the Knowledge Economy*. https://doi.org/10.1007/s13132-024-01881-5

Li, G., Luo, T., & Song, Y. (2022). Spatial equity analysis of urban public services for electric vehicle charging—Implications of Chinese cities. *Sustainable Cities and Society*, *76*. https://www.sciencedirect.com/science/article/pii/S221067072100785X

Liao, F., Molin, E., & van Wee, B. (2017). Consumer preferences for electric vehicles: A literature review. *Transport Reviews*, *37*(3), 252–275.

Malarkey, D., Singh, R., & MacKenzie, D. (2023). *Customer Experience at Public Charging Stations and Its Effects on the Purchase and Use of Electric Vehicles* (INL/RPT-23-74951-Rev000). Idaho National Laboratory (INL), Idaho Falls, ID (United States); Argonne National Laboratory (ANL), Argonne, IL (United States); National Renewable Energy Laboratory (NREL), Golden, CO (United States). https://doi.org/10.2172/2293486

Mersky, A. C., Sprei, F., Samaras, C., & Zhen, Q. (Sean). (2016). Effectiveness of incentives on electric vehicle adoption in Norway—ScienceDirect. *Transportation Research Part D: Transport and Environment*, *46*, 56–68.

Mogile Technologies, Inc. (2021). *Identification of Current and Future Infrastructure Deployment Gaps*. Natural Resources Canada.

Mogile Technologies, Inc. (2022). *Biennial Snapshot of Canada's Electric Charging Network and Hydrogen Refuelling Stations for Light-Duty Vehicles* (NRCan-5000062968). Natural Resources Canada.

MotorTrend. (2023, January 27). *Road-Tripping in Our Long-Term EV Test Cars Has Been … Interesting*. MotorTrend. https://www.motortrend.com/reviews/road-tripping-in-our-long-term-electric-test-cars/

Münzel, C., Plötz, P., Sprei, F., & Gnann, T. (2019). How large is the effect of financial incentives on electric vehicle sales? *Energy Economics*, *Volume 84*(104493). https://www.sciencedirect.com/science/article/pii/S0140988319302749

NACS. (2024, January 23). *U.S. Convenience Store Count*. https://www.convenience.org/Research/Convenience-Store-Fast-Facts-and-Stats/FactSheets/IndustryStoreCount

Ojiaku, O. C., & Osarenkhoe, A. (2018). Determinants of Customers' Brand Choice and Continuance Intentions with Mobile Data Service Provider: The Role of Past Experience. *Global Business Review*, *19*(6), 1478–1493. https://doi.org/10.1177/0972150918780764

Okoma, M. (2023). *The impact of Electric Vehicle Charging Stations on Light Duty Electric Vehicle adoption and rebates California.* EVS36, Sacramento, CA.

Pamidimukkala, A., Kermanshachi, S., Rosenberger, J. M., & Hladik, G. (2024). Barriers and motivators to the adoption of electric vehicles: A global review. *Green Energy and Intelligent Transportation*, *3*(2), 100153. https://doi.org/10.1016/j.geits.2024.100153

Pan, L., Yao, E., & MacKenzie, D. (2019). Modeling EV charging choice considering risk attitudes and attribute non-attendance. *Transportation Research Part C: Emerging Technologies*, *102*, 60–72.

Plug In America. (2023). *2023 EV Driver Survey*. https://pluginamerica.org/survey/2023-ev-driver-survey/

Qian, L., & Soopramanien, D. (2011). Heterogeneous consumer preferences for alternative fuel cars in China. *Transportation Research Part D: Transport and Environment*, *16*(8), 607–613. https://doi.org/10.1016/j.trd.2011.08.005

Randall, T. (2023, March 9). US Electric Cars Set Record With Almost 300-Mile Average Range. *Bloomberg.Com*. https://www.bloomberg.com/news/articles/2023-03-09/average-range-for-us-electric-cars-reached-a-record-291-miles

Rasouli, S., & Timmermans, H. (2014). Judgments of travel experiences, activity envelopes, trip features and multi-tasking: A panel effects regression model specification. *Transportation Research Part A: Policy and Practice*, *63*, 67–75. https://doi.org/10.1016/j.tra.2014.02.012

Rempel, D., Cullen, C., Bryan, M. M., & Cezar, G. V. (2022). *Reliability of Open Public Electric Vehicle Direct Current Fast Chargers* (SSRN Scholarly Paper 4077554). https://doi.org/10.2139/ssrn.4077554

Rika, M. (2024, March 6). US EV Market Passed the 1 Million Sales Mark in 2023. *Statzon*. https://statzon.com/insights/us-ev-market

Shin, D.-H. (2015). Effect of the customer experience on satisfaction with smartphones: Assessing smart satisfaction index with partial least squares. *Telecommunications Policy*, *39*(8), 627–641. https://doi.org/10.1016/j.telpol.2014.10.001

Sierzchula, W., Bakker, S., Maat, K., & van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*, 183–194. https://doi.org/10.1016/j.enpol.2014.01.043

Sprei, F., & Kempton, W. (2024). Mental models guide electric vehicle charging. *Energy*, *292*, 130430. https://doi.org/10.1016/j.energy.2024.130430

Tanaka, M., Ida, T., Murakami, K., & Friedman, L. (2014). Consumers' willingness to pay for alternative fuel vehicles: A comparative discrete choice analysis between the US and Japan. *Transportation Research Part A: Policy and Practice*, *70*, 194–209. https://doi.org/10.1016/j.tra.2014.10.019

Train, K. E. (2009). Endogeneity. In *Discrete Choice Methods with Simulation* (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511805271

Train, K. E., & Winston, C. (2007). Vehicle Choice Behavior and the Declining Market Share of U.S. Automakers. *International Economic Review*, *48*(4), 1469–1496.

Traut, E. J., Cherng, T. C., Hendrickson, C., & Michalek, J. J. (2013). US residential charging potential for electric vehicles. *Transportation Research Part D: Transport and Environment*, *25*, 139–145. https://doi.org/10.1016/j.trd.2013.10.001

Tucker, S. (2023, October 13). *Report: Broken Public Chargers Challenge EV Owners*. Kelley Blue Book. https://www.kbb.com/car-news/report-broken-public-chargers-challenge-ev-owners/

U.S. Census Bureau. (2020). *American Community Survey 5-Year Data (2009-2022)*. Census.Gov. https://www.census.gov/data/developers/data-sets/acs-5year.html

U.S. Census Bureau. (2022). *DP04: Selected Housing Characteristics—Census Bureau Table*. https://data.census.gov/table/ACSDP1Y2022.DP04?q=home%20ownership

U.S. Department of Energy. (2024, May 14). *Alternative Fueling Station Counts by State*. Alternative Fuels Data Center. https://afdc.energy.gov/stations/states

Valeri, E., & Danielis, R. (2015). Simulating the market penetration of cars with alternative fuelpowertrain technologies in Italy. *Transport Policy*, *37*, 44–56. https://doi.org/10.1016/j.tranpol.2014.10.003

Vij, A., & Walker, J. L. (2016). How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B: Methodological*, *90*, 192–217. https://doi.org/10.1016/j.trb.2016.04.021

Wang, Y., Yao, E., & Pan, L. (2021). Electric vehicle drivers' charging behavior analysis considering heterogeneity and satisfaction. *Journal of Cleaner Production*, *286*, 124982. https://doi.org/10.1016/j.jclepro.2020.124982

White, L. V., Carrel, A. L., Shi, W., & Sintov, N. D. (2022). Why are charging stations associated with electric vehicle adoption? Untangling effects in three United States metropolitan areas. *Energy Research & Social Science*, *89*, 102663. https://doi.org/10.1016/j.erss.2022.102663

Wolfe, R. (2022). *I rented an electric car for a 4-day road trip. I spent more time charging it than I did sleeping.* Fox Business. https://www.foxbusiness.com/lifestyle/electric-car-four-day-trip-more-time-charging-sleeping

Worsley, A. (1989). Perceived reliability of sources of health information. *Health Education Research*, *4*(3), 367–376. https://doi.org/10.1093/her/4.3.367

Zang, Z., Xu, X., Qu, K., Chen, R., & Chen, A. (2022). Travel time reliability in transportation networks: A review of methodological developments. *Transportation Research Part C: Emerging Technologies*, *143*. https://www.sciencedirect.com/science/article/pii/S0968090X22002820?casa_token=BGBbD5kydI4AAAAA:HdbqMYL9CICh8Khywu_ysIC_y-7R4MuLBRQEDIu7XleiH_8dq0nNZU-fq7kHpZVe_iA7ND00-A

Zou, T., Khaloei, M., & MacKenzie, D. (2020). Effects of Charging Infrastructure Characteristics on Electric Vehicle Preferences of New and Used Car Buyers in the United States.

Transportation Research Record, *2674*(12), 165–175.
https://doi.org/10.1177/0361198120952792

APPENDIX A: FULL QUESTIONNAIRE

Section 1

We will begin the survey with demographic questions for statistical purposes. Your responses will be kept confidential and we have designed the survey such that there is no way to identify you from your responses.

What is your age?

What is your gender?

- Male
- Female
- Non-binary
- Not listed here

What is your race? Select all that apply.

- ☐ White
- ☐ Black or African American
- ☐ American Indian or Alaska Native
- ☐ Asian
- ☐ Native Hawaiian or Pacific Islander
- ☐ Middle Eastern or North African
- ☐ Hispanic or Latino
- ☐ Not listed here

→

How many people live in your household* including yourself?

*Your household includes people living with you and sharing income with you (e.g., spouse, partner, or dependents)

Of the people in your household, how many are children under 18?

*Your household includes people living with you and sharing income with you (e.g., spouse, partner, or dependents)

What is the zip code where you currently live?

← →

What is the highest degree or level of school you have completed?

- ◯ Less than High School
- ◯ High School Graduate or GED
- ◯ Some College/Technical School Training
- ◯ 2-Year College Degree (Associates)
- ◯ 4-Year College Degree (B.A., B.S.)
- ◯ Master's Degree
- ◯ Doctoral Degree
- ◯ Professional Degree (M.D., J.D.)

Which of the following best describes your current employment status?

- ◯ Employed, Full-Time (35+ hours/week)
- ◯ Employed, Part-time (Fewer than 35 hours/week)
- ◯ Homemaker
- ◯ Looking for work
- ◯ Unable to work due to a disability
- ◯ Retired
- ◯ Unemployed
- ◯ Another

Section 2

The next part of the survey will include questions about your vehicle purchasing history.

In your household, who is the primary decision-maker for purchasing or leasing a vehicle?
*Your household includes people living with you and sharing income with you (e.g. spouse, partner, or dependents)

- ◯ I am
- ◯ Another household member
- ◯ Another household member and I decide together

Have you or anyone in your household* owned or leased a plug-in electric vehicle?
*Your household includes people who both live with you and share income with you (e.g., spouse, partner, or dependents)

- ◯ I, or someone in my household, have owned or leased a plug-in electric vehicle.
- ◯ I, or someone in my household, have not owned or leased a plug-in electric vehicle.

→

How many passenger vehicles are owned, leased, or available for regular use by you and the people who live in your household*?
*Your household includes people who both live with you and share income with you (e.g. spouse, partner, or dependents)

[ ]

→

Which category best describes your household* income before taxes from the last calendar year?

*Your household includes yourself and the people who both live with you and share income with you (e.g., spouse, partner, or dependents)

- ◯ Under $10,000
- ◯ $10,000 – $14,999
- ◯ $15,000 – $19,999
- ◯ $20,000 – $24,999
- ◯ $25,000 – $34,999
- ◯ $35,000 – $49,999
- ◯ $50,000 – $74,999
- ◯ $75,000 – $99,999
- ◯ $100,000 – $149,999
- ◯ $150,000 – $199,999
- ◯ $200,000 – $249,999
- ◯ $250,000 or more
- ◯ Prefer not to answer

→

How many passenger vehicles are owned, leased, or available for regular use by you and the people who live in your household*?

*Your household includes people who both live with you and share income with you (e.g. spouse, partner, or dependents)

→

What year did you last purchase or lease a vehicle?

On average, how many times per month do you purchase gas?

- More than 4 Times per Month
- 3-4 Times per Month
- 1-2 Times per Month
- Less than Once per Month

← →

For what purposes do you use your car? Check all that apply

- [ ] Commuting to work
- [ ] Running errands
- [ ] Driving locally
- [ ] Extended road trips
- [ ] Another

How often do you make a driving trip to a destination more than 2 hours away from where you currently live?

- ( ) More than Once per Month
- ( ) Once per Month
- ( ) Multiple Times per Year
- ( ) Less than Once per Year
- ( ) Never

← →

For what purposes do you use your car? Check all that apply

- [ ] Commuting to work
- [ ] Running errands
- [ ] Driving locally
- [ ] Extended road trips
- [ ] Another

How often do you make a driving trip to a destination more than 2 hours away from where you currently live?

- ○ More than Once per Month
- ○ Once per Month
- ○ Multiple Times per Year
- ○ Less than Once per Year
- ○ Never

← →

Based on your experience with gas stations, fill in the following statement.

"I think gas stations provide ________ service."

- Very Unreliable
- Unreliable
- Somewhat Unreliable
- Somewhat Reliable
- Reliable
- Very Reliable

← →

Do you own or rent your home?

- ◯ Own
- ◯ Rent
- ◯ Some other arrangement

Where do you primarily park at home?

- ◯ An Attached Private Garage
- ◯ A Detached Private Garage
- ◯ A Driveway or Carport
- ◯ An Assigned Parking Space in a Shared Lot or Garage
- ◯ An Unassigned Parking Space in a Shared Lot or Garage
- ◯ On Street

When do you plan to move out from your current home?

- ◯ Less than 2 years
- ◯ In the next 2-5 years
- ◯ In more than 5 years
- ◯ I do not plan to move out from my current home
- ◯ Not sure

← →

Section 3

We would now like you to imagine you are shopping for the next vehicle you plan to purchase or lease.

→

Would you be more likely to acquire a new or used vehicle?

- New
- Used

What is the maximum total amount you anticipate spending on your next car purchase or lease?

$

←

→

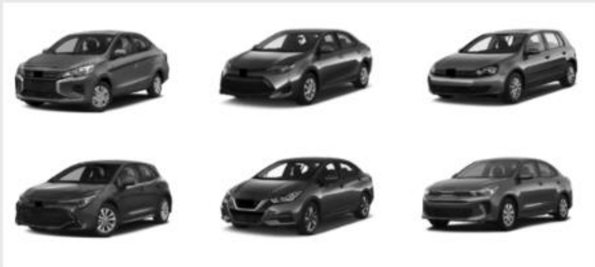
Which of the following vehicle types would you be most interested in purchasing or leasing?

- Car
- SUV
- Pickup Truck
- Minivan
- Passenger Van

→

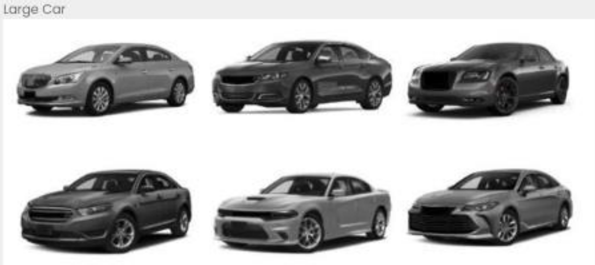
If you were shopping for a car, which **size** car would you be most interested in purchasing?

Small Car



Midsize Car

Large Car



← →

Based on **appearance only**, which of the small cars would you be most likely to buy?

←

→

If you were shopping for a pickup truck, which **size** pickup truck would you be most interested in purchasing?

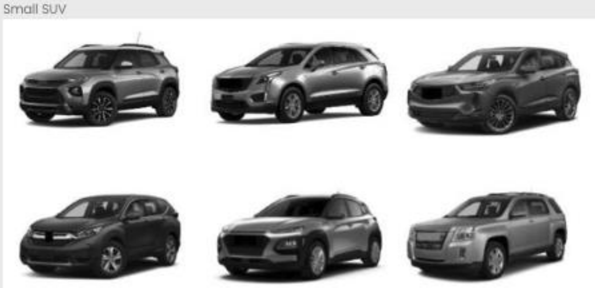
○ Small Pickup Truck

○ Standard Pickup Truck

← →

If you were shopping for a SUV, which **size** SUV would you be most interested in purchasing?

○ Small SUV



○ Standard SUV

← →

Based on **appearance only**, which of the minivans would you be most likely to buy?

← →

Based on **appearance only**, which of the passenger vans would you be most likely to buy?

←　　→

You have selected this vehicle design:

This image will be used for the next sections. If the vehicle above is not the one you wanted, click the "Back" button on the web browser and select a different image. Otherwise, click "next" below.

←　　→

Section 4

We will now provide some introductory information about electric vehicles. Please read the passage carefully as you will need to answer comprehension questions correctly to proceed to the remainder of the survey.

→

Most electric vehicle drivers charge at home for day-to-day use, and use public charging stations for longer trips. Drivers who can't charge at home or work tend to rely on public charging stations for day-to-day use as well as for longer trips. This includes those who park on the street, in shared lots or parking structures, or who cannot install a charger at home.

Drivers who have private parking are much more likely to ________ for day-to-day use.

- ○ Rely on Public Charging
- ○ Charge at Home

← →

Your answer was not correct. Please review the passage and answer the following question again.

Most electric vehicle drivers **charge at home for day-to-day use**, and **use public charging stations for longer trips**. Drivers who can't charge at home or work tend to rely on public charging stations for day-to-day use as well as for longer trips. This includes those who park on the street, in shared lots or parking structures, or who cannot install a charger at home.

Drivers who have private parking are much more likely to ________ for day-to-day use.

- ○ Rely on Public Charging
- ○ Charge at Home

← →

Drivers who do not have dedicated or private parking are much more likely to ________ for both day-to-day use and longer trips.

- ◯ Rely on Public Charging
- ◯ Charge at Home

← →

Drivers on long distance trips are likely to ________.

- ◯ Rely on Public Charging
- ◯ Charge at Home

← →

Drivers like you who **Rent their Home** and **Park in A Driveway or Carport** are likely to ________ **for day-to-day use.**

- ◯ Rely on Public Charging
- ◯ Charge at Home

← →

Section 5

We will now provide some information about the reliability of public chargers for electric vehicles. Please read the passage carefully.

→

Picture a world where public charging stations are **routinely out-of-service** or **fail to operate correctly.** Charging equipment may be broken, payment systems reject drivers' credit cards, there are long lines, or for any other reason, **drivers are frequently unable to charge their vehicle** at a station.

These issues can **leave electric vehicle drivers stranded** if there is no other functioning station nearby. Drivers must research not only where charging stations are, but whether they are currently working or not - and the answer may change before they arrive.

→

Based on the description above, how would you rate the reliability of electric vehicle public chargers from 0 (worst) - 100 (best)?

0 10 20 30 40 50 60 70 80 90 100

Reliability of Electric Vehicle Public Chargers

Based on the description above, fill in the following statement.

"I think electric vehicle public charging stations provide _______ service."

- ○ Very Unreliable
- ○ Unreliable
- ○ Somewhat Unreliable
- ○ Somewhat Reliable
- ○ Reliable
- ○ Very Reliable

Based on the description above, would you agree or disagree with the following statement?

"I can depend on the service provided by electric vehicle public charging stations."

- Strongly Agree
- Agree
- Somewhat Agree
- Somewhat Disagree
- Disagree
- Strongly Disagree

Based on the description above, how would you feel about electric vehicle public chargers working as they are intended to?

- Very Doubtful
- Doubtful
- Somewhat Doubtful
- Somewhat Confident
- Confident
- Very Confident

Suppose you had to depend on an electric vehicle public charger to complete an essential trip. Based on the description above, how comfortable would you be relying on the charger?

- ◯ Very Comfortable
- ◯ Comfortable
- ◯ Somewhat Comfortable
- ◯ Somewhat Uncomfortable
- ◯ Uncomfortable
- ◯ Very Uncomfortable

← →

Based on what you know about electric vehicle public chargers, how would you rate the reliability of electric vehicle public chargers from 0 (worst) - 100 (best)?

0 10 20 30 40 50 60 70 80 90 100

Reliability of Electric Vehicle Public Chargers

Based on what you know about electric vehicle public chargers, fill in the following statement.

"I think electric vehicle public charging stations provide _______ service."

- ◯ Very Unreliable
- ◯ Unreliable
- ◯ Somewhat Unreliable
- ◯ Somewhat Reliable
- ◯ Reliable
- ◯ Very Reliable

Based on what you know about electric vehicle public chargers, would you agree or disagree with the following statement?

"I can depend on the service provided by electric vehicle public charging stations."

- Strongly Agree
- Agree
- Somewhat Agree
- Somewhat Disagree
- Disagree
- Strongly Disagree

Based on what you know about electric vehicle public chargers, how would you feel about electric vehicle public chargers working as they are intended to?

- Very Doubtful
- Doubtful
- Somewhat Doubtful
- Somewhat Confident
- Confident
- Very Confident

Suppose you had to depend on an electric vehicle public charger to complete an essential trip. Based on what you know about electric vehicle public chargers, how comfortable would you be relying on the charger?

- Very Comfortable
- Comfortable
- Somewhat Comfortable
- Somewhat Uncomfortable
- Uncomfortable
- Very Uncomfortable

→

Picture a world in which public charging stations **operate flawlessly in every respect.** Payments are seamless, equipment is in working order, and electric vehicle drivers can **charge successfully on the first try, every time.** This makes it convenient, even during long trips or when electric vehicle drivers can't charge at home.

Electric vehicle drivers can charge with confidence whenever they are at a public charging station.

→

Section 6

We will now ask you some questions about certain vehicle features, which are explained below. Please read the descriptions carefully before moving forward in the survey.

Price

The final price paid for the vehicle in dollars, including all taxes and fees, and after subtracting any incentives.

Vehicle Types

Conventional: Gasoline engine only.
Electric: Electric motor only. Must be plugged in to be charged.

Operation Cost

Cost of fueling per 100 miles of driving.

Range

The distance the vehicle can travel before needing to be refueled.

Charging Availability

The amount of public charging stations available for fueling electric vehicles. This is displayed as a percentage of the total number of gas stations.

→

For the next section, we will show you two vehicles for sale, and you should select the choice you would be most likely to buy, assuming they are the only available choices on the market.

Each option will look like this. Both options are **entirely identical** in look and functionality apart from the described attributes.

In all cases, electric vehicle public chargers are like those you characterized as

Note that some of the options are likely to be vehicles you have not seen in the current market, but may become available in the future. **You should respond as if they were available today.**

You will be asked 10 questions total in this section.

For the next section, we will show you two vehicles for sale, and you should select the choice you would be most likely to buy, assuming they are the only available choices on the market.

Each option will look like this. Both options are **entirely identical** in look and functionality apart from the described attributes.

In all cases, electric vehicle public chargers are like those you characterized as **VERY UNRELIABLE**

Note that some of the options are likely to be vehicles you have not seen in the current market, but may become available in the future. **You should respond as if they were available today.**

You will be asked 10 questions total in this section.

← →

Question 1/10

Suppose these two vehicles below were the only vehicles available for purchase. Which would you choose?

Both options are **entirely identical** in look and functionality apart from the described attributes.

In this situation, imagine that electric vehicle public chargers are like those described earlier, which you characterized as:

VERY UNRELIABLE

	Option 1	**Option 2**
		
New or Used?	Used	Used
Vehicle Type	Electric	Gasoline
Purchase Price	$32,000	$36,000
Range	200	400
Operating Cost	$7.50 per 100 miles	$12.50 per 100 miles
Public Fueling/Charging Availability	25% of existing gas stations 	100% of existing gas stations 
Public Fueling/Charging Reliability	Very Unreliable	Reliable
Home Fueling/Charging Available?	No	No

	Option 1	Option 2
Your choice:	○	○

→

Great! You are done with the choice questions and will now proceed to some background questions.

→

Section 7

Thank you so much for your help! Please read the following statements carefully and answer according to your own experiences. After this section, we will be finished.

← →

Would you agree or disagree with the following statement?

"New technologies do not scare me at all."

- ◯ Strongly agree
- ◯ Agree
- ◯ Neutral
- ◯ Disagree
- ◯ Strongly disagree

Would you agree or disagree with the following statement?

"In general, I am among the first in my circle of friends to buy a new technology when it appears."

- ◯ Strongly agree
- ◯ Agree
- ◯ Neutral
- ◯ Disagree
- ◯ Strongly disagree

Would you agree or disagree with the following statement?

"I must be certain that a new idea does not fail before I adopt."

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

← →

Would you agree or disagree with the following statement?

"New technologies make me feel uncomfortable."

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Would you agree or disagree with the following statement?

"I am a very late adopter of in-car bluetooth technology."

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Would you agree or disagree with the following statement?

"I am suspicious of agents of change (e.g. people who like change, speak with you about change, try to promote change)."

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Would you agree or disagree with the following statement?

"I believe resistance to innovation is entirely rational."

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

← →

Would you agree or disagree with the following statement?

"I am one of the last to adopt in-car bluetooth technology."

- ◯ Strongly agree
- ◯ Agree
- ◯ Neutral
- ◯ Disagree
- ◯ Strongly disagree

Would you agree or disagree with the following statement?

"I approach innovations with a skeptical and cautious air."

- ◯ Strongly agree
- ◯ Agree
- ◯ Neutral
- ◯ Disagree
- ◯ Strongly disagree

Would you agree or disagree with the following statement?

"I often fear high-tech a little bit."

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Would you agree or disagree with the following statement?

"I am always seeking new technologies."

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

← →

We thank you for your time spent taking this survey.

Your response has been recorded.

APPENDIX B: ADDITIONAL RESULTS

2SLS Results

Using the factor scores, we conducted the 2SLS analysis, first in steps, and then simultaneously. We did not include any covariates in the first step. The outcome of the first-step model was the reliability factor scores, predicted by an intercept term and the two dummy instrumental variables, assignment to the high treatment group and assignment to the low treatment group.

The outcome variable of the reduced form model was stated choice, a binary variable (0: ICEV, 1: EV), but modeled as linear. The reduced form model included estimates for the attributes of each alternative and uses the fitted reliability factor scores from the first-step in the model. Finally, the 2SLS model was estimated simultaneously to ensure appropriate standard errors. The results of the 2SLS estimation are in Table 9.

TABLE 9 2SLS Estimation Results

Variable	**First-Step**		**Reduced Form**		**Simultaneous Estimation**	
Outcome	Reliability Factor Scores		Stated Choice (EV = 1, ICEV = 0)		Stated Choice (EV = 1, ICEV = 0)	
	Value	Std. Error	Value	Std. Error	Value	Std. Error
Intercept	0.062	0.000	0.1802	0.044	0.162	0.042
Perceived Reliability Factor Scores (Fitted)	-	-	-	-	0.098	0.006
EV Price (Multipier: Price Shown / Budget)	-	-	-0.4295	0.031	-0.429	0.030
EV Operating Cost ($/100 miles)	-	-	-0.0130	0.001	-0.013	0.001
EV Range (miles)	-	-	0.0004	0.000	0.000	0.000
EV Charging Availability	-	-	0.0024	0.000	0.002	0.000
ICEV Price (Multiplier: Price Shown / Budget)	-	-	0.3958	0.031	0.397	0.030
ICEV Operating Cost ($/100 miles)	-	-	0.0119	0.001	0.012	0.001
ICEV Range (miles)	-	-	-0.0003	0.000	-0.003	0.000
High Treatment	0.573	0.015	0.0475	0.008	-	-
Low Treatment	-0.758	0.016	-0.0824	0.008	-	-
R-Squared	0.312		0.091		0.162	
F-Statistic	6848		173		1786	
P-Value (F-Stat)	0.00		0.00		0.00	