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Poor Reliability of Public Charging Stations Can Impede the Growth of the Electric Vehicle Market

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Executive Summary

How does the reliability of public charging infrastructure affect electric vehicle (EV) adoption? Substantial public and private investments are expanding EV charging networks, but concerns are growing about the poor reliability of existing chargers and its potential impacts on EV adoption. Using data from a nationwide survey, we employ a choice model to quantify the effects of perceived charging reliability on Americans' intentions to purchase new or used EVs. By randomly assigning participants to receive information characterizing public charging as either very reliable or very unreliable, we show a causal effect of reliability perceptions on EV purchase intentions. We find that differences in perceived reliability are equivalent to a 32% purchase price change or 366 miles of range, underscoring the importance of reliable public charging.

Keywords: electric vehicles, consumer behaviour, consumer demand, public policy and promotion, trends & forecasting of e-mobility

1 Introduction

The market for electric vehicles (EVs) in the United States has been growing rapidly, driven by a combination of technological advancements and supportive public policies. From 2022 to 2023, the EV market share expanded from 5.9% to 7.6% [1]. Additionally, 17 states have mandated that all new light-duty vehicles sold emit zero emissions by 2035 [2]. Sustaining this growth and meeting regulatory mandates requires that EVs become acceptable to all consumers. Despite early trends, the transition to electric vehicles faces significant challenges as the market moves beyond early adopters [3], [4]

Extensive research has identified the factors that affect EV adoption and make EVs more acceptable to future consumers. Prior work has consistently highlighted the importance of having public chargers available [5], [6], [7], [8] and under the 2021 Bipartisan Infrastructure Law, $7.5 billion of federal funding has been dedicated to developing public charging infrastructure [9]. However, in recent years, concerns about the reliability of public chargers have been increasing [10], [11]. Numerous media reports emphasize the challenges faced due to unreliable public charging stations, particularly during long road trips [12], [13], [14]. As negative experiences with public charging accumulate and become more widely known, they may deepen potential buyers' reluctance to purchase an EV. This has motivated a federal response, and the recent $100 million investment in enhancing charging infrastructure reliability [15] and the establishment of the National Charging Experience Consortium (ChargeX) [10] along with minimum standards for federally funded stations [16] represent concerted efforts to address EV charging challenges.

Still, there is a very limited understanding of the effect of public charging reliability on the decisions to purchase or retain an EV [10]. While many reports and studies characterize the current levels of public charging reliability [17], [18], [19] and the factors affecting EV adoption [20], [21], [22], [23], [24], [25], [26], [27], [28], there is a notable gap in the evidence linking these two dimensions. This paper uses a discrete choice model to identify how subjective perceptions of public charging reliability influence EV purchase decisions among people who do not yet have an EV. We focus on non-EV owners since many existing EV owners tend to be tolerant of charging challenges [11], [29]. Finally, recognizing that absolute charging reliability will not always be attainable, we evaluate the impact of differing reliability perceptions on consumers' willingness to buy EVs, highlighting the urgency of improving charging infrastructure to achieve widespread adoption and meet environmental goals.

2 Data

2.1 Data Collection Approach

To establish a causal link between perceived reliability and willingness to purchase an EV, we surveyed Americans who did not own an EV in March and April 2024. The survey included a stated choice experiment in which respondents chose between comparable electric and gasoline vehicles, with systematically controlled variation in the attributes of each vehicle. While stated choice experiments are limited in that they deal in hypotheticals, rather than actual behavior, they allow us to infer causality and evaluate purchasing behaviors in situations that may not yet exist (e.g., widespread public charging infrastructure, various levels of public charging reliability) [20].

After some introductory questions about their background and their current primary vehicle, the respondents were prompted to envision themselves shopping for the next vehicle they planned to purchase or lease, and were asked to report their maximum budget. Following this, they were asked to select their desired vehicle type, size, and aesthetic from a set of stock images. The same vehicle image was shown as both the EV and conventional option to emphasize to respondents that the vehicles were identical apart from the presented attributes, as done in [20].

The respondents were then 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 stations and public charging stations.

Since the roles of home charging and public charging are crucial to how public charging reliability may affect experiences as an EV owner, the survey introduced respondents to both types of charging and typical use cases, providing background information along with comprehension checks. The introduction shown was as follows: "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." They were then asked the following three comprehension questions and prompted to re-answer if they responded incorrectly. If they responded incorrectly a second time, they were removed from the survey.

(1) "Drivers who have private parking are much more likely to _____ for day-to-day use." [Rely on Public Charging / Charge at Home]

(2) "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]

(3) "Drivers on long-distance trips are likely to _____" [Rely on Public Charging / Charge at Home]

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. This response was shown in the choice exercises as the respondents' access to home charging.

(4) "Drivers like you who own their home and park in an attached garage are likely to _____ for day-to-day use." [Rely on Public Charging / Charge at Home]

2.2 Treatment and Measurement of Perceived Reliability

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. The randomization of assignment ensures that differences in perceived reliability between groups are uncorrelated with respondent characteristics, prior perceptions, or general beliefs about EVs. This approach allows us to identify causal relationships between treatment group assignment, reliability perceptions, and stated willingness to choose an EV.

The low treatment group was shown the following vignette (bolding in original): “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." While most visits to charging stations tend to end successfully [30], the conditions as described arguably represent the current experience reported by many EV drivers in the US [12], [13], [14].

The high treatment group was shown the following (bolding in original): “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 given any instruction about the conditions of public charging; rather, they were asked about their perceptions of reliability based on what they already knew. Following the treatment, respondents were presented with indicator questions aimed at measuring the latent variable "perceived reliability”.

2.3 Stated Preference Experiment

The respondents were then asked to choose between an EV and a conventional vehicle in 10 different scenarios, with varying vehicle and infrastructure attributes (an example of one scenario is shown in Figure 1).

The attributes that varied among the choice sets were price, range, operating cost, and EV charging availability. These choice tasks were generated using an optimal fractional design, calculated using Federov’s exchange algorithm [31], 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 each.

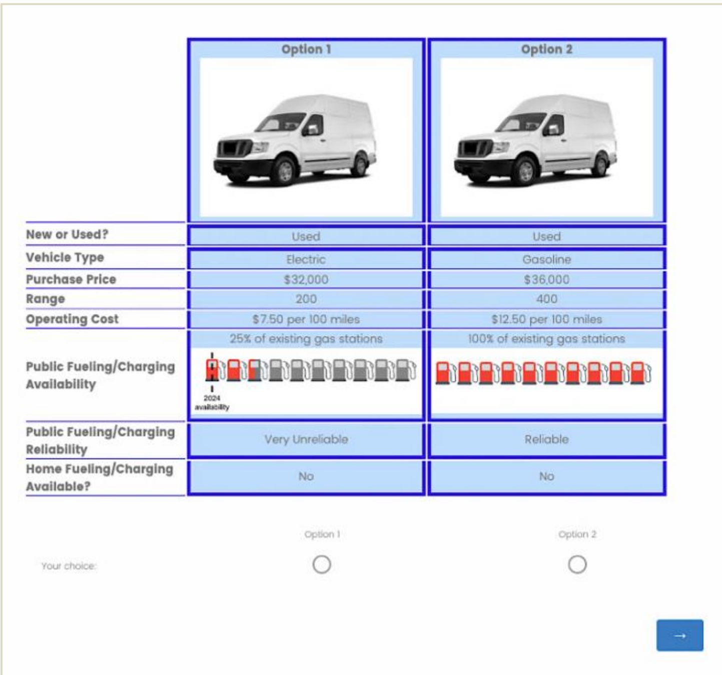

Figure 1: Sample choice experiment incorporating both experimentally designed attributes and respondent’s previous answers

2.4 Summary Statistics

We used Dynata's online panel, which offers benefits over other platforms for achieving representativeness [20], [32], to recruit respondents from across the US. After cleaning the data for respondents whose responses to choice exercises were not recorded properly, the final sample size was 1,569 respondents. Table 1 shows the summary statistics of the sample before and after cleaning and compared to the national population.

Table 1: Summary statistics of sample compared with [33]

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%
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%	-
What is the maximum total amount you anticipate spending on your next car purchase or lease?	Used	Mean: $19,603	Mean: $19,767	Mean: $25,638[1]
	New	Mean: $39,178	Mean: $39,290	Mean: $47,218[2]
Treatment Group Assignment	Low Reliability Group	33.2%	33.2%	-
	High Reliability Group	34.0%	34.0%	-
	Control	32.8%	32.8%	-
Total Count		1633 Responses	1569 Responses	

3 Methods

3.1 Methodology Overview

We analyzed respondents' choices using an integrated choice and latent-variable model (ICLV), while accounting for the correlations across individual observations. The ICLV framework has three main components, the structural model, the measurement model, and the discrete choice model. These three parts

[1] Average used vehicle listing price is based on February 2024 data [35]
[2] Average new vehicle listing price is based on March 2024 data [36]

are simultaneously estimated to capture the influences of the latent endogenous variables and other explanatory variables on EV purchase choices.

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 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 [37] and integrated it with the ICLV framework [38] 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 modeling framework is shown in Figure 2. This approach allowed us to uncover the relative importance of the different factors influencing EV purchase decisions, with a focus on the subjective perceptions of reliability. Crucially, it allows us to identify the causal effect of perceived reliability on EV purchase intention, exploiting the randomized assignment of respondents to the low treatment, high treatment, and control groups.

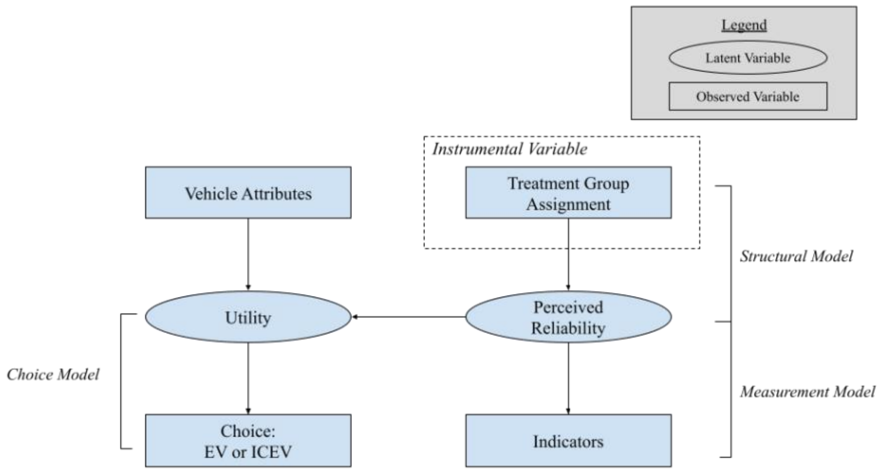

Figure 2: Modeling Framework

3.2 Structural Model

The structural model is based on the first step of the 2SLS analysis. The perceived reliability latent variable R for individual i is modeled as shown in Eq. 1.

$$R_i = \gamma_0 + \gamma_l z_i + \xi_i \qquad (1)$$

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

3.3 Measurement Model

There are four indicators used in the measurement model, all with 6-level ordinal responses. These observed variables are used to infer the value of the latent (unobservable) construct of perceived reliability, and are linked to perceived reliability by an ordered probit model.

The probability of a given response I for individual i is estimated by the ordered probit model, as shown in Eqs. 2 and 3.

$$I_i^* = \delta R_i + \nu_i,\ \nu_i \sim N(0, \sigma_\nu) \quad (2)$$

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

where I_i^* is the continuous indicator for latent variable R_i that underlies the discrete responses I_i. I_i^* is predicted by the perceived reliability latent variable R_i with coefficient δ, 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:

$$P_i(I_i = k) = \phi\left(\frac{\tau_k - \delta R_i}{\sigma_\nu}\right) - \phi\left(\frac{\tau_{k-1} - \delta R_i}{\sigma_\nu}\right) \quad (4)$$

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

3.4 Choice Model

We evaluated mode choices between EVs and ICEVs using the random utility maximization (RUM) framework, accounting for correlations across individual observations. Our utility function specification is shown in Eq. 5.

$$U_{ij} = ASC_j + \beta_j X_{ij} + \theta_j R_i + \sigma_j \xi_{ij} + \varepsilon_{ij} \quad (5)$$

where U_{ij} is the utility of vehicle j for individual i, ASC_j is the alternative specific constant (ASC) for vehicle j, β_j is the vector of coefficients of observed predictors, X_{ij} are the observed predictors, θ_j is the coefficient of the latent variable, R_i is the latent variable perceived reliability, $\sigma_j \xi_{ij}$ is an error component that induces correlation in choices by respondent i across alternatives of type j, and ε_{ij} is the i.i.d. Gumbel distributed error term.

4 Results

4.1 Full Model Results

The results of the choice model, the structural model, and the measurement model are presented in Table 2.

Table 2: Integrated choice and latent variable (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

Variable	Value	Std. Error
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	

4.2 Impact of Public Charging Reliability on EV Purchase Decisions

The effect of the reliability of public EV charging infrastructure was positive and statistically significant in the ICLV model for respondents with and without access to home charging (Table 2). This indicates that higher perceived reliability causes an increased willingness to adopt EVs. Figure 3 illustrates the coefficient estimate of perceived reliability of public charging for respondents with and without home charging. The effect was not statistically different for users without home charging although they are more likely to be reliant on public chargers for day-to-day use.

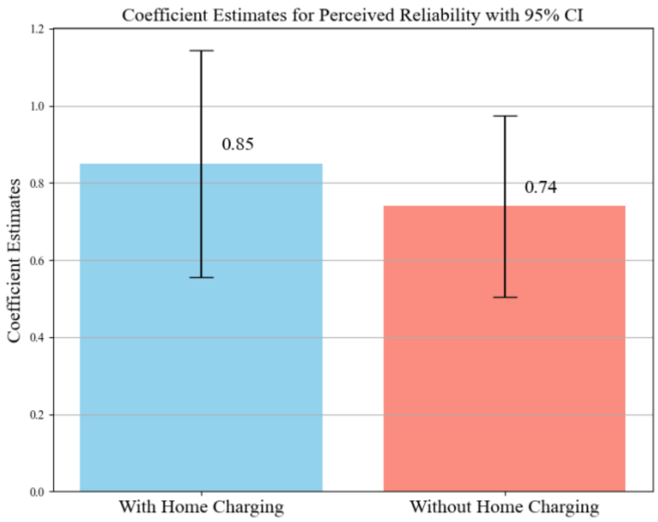

Figure 3: Effect of perceived public charging reliability on EV purchase decisions for respondents with and without home charging

4.3 Varying Perceptions of Reliability Across Treatment Groups

Figure 4 illustrates how perceived reliability varied across treatment groups. In the absence of specific information, respondents in the control group reported reliability perceptions that were closer to those of the high treatment group than to the low treatment group. This suggests that non-EV owners may have a more optimistic view of the reliability of public chargers than what many EV drivers experience today. If their perceptions were adjusted, reducing perceived reliability by the difference observed between the low treatment group and the control group, we would expect a change in the willingness to purchase an EV.

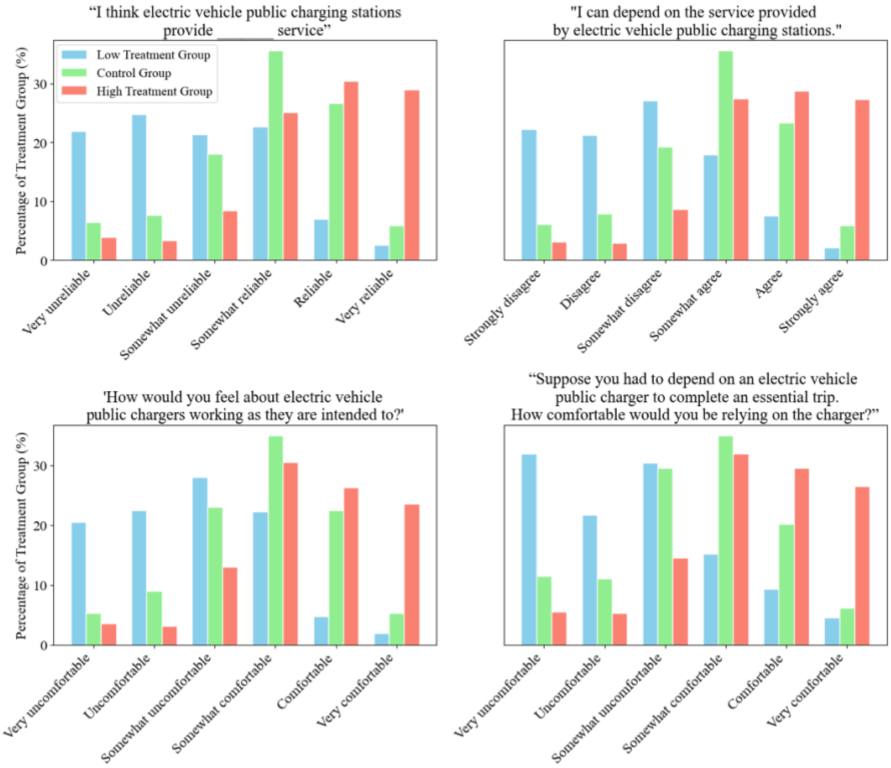

Figure 4: Distribution of responses to indicator questions measuring public charging reliability by treatment group.

4.4 Effects of Worsening Perceptions of Charging Reliability

To clarify the effect of public charging reliability on EV purchase decisions, we consider how worsened reliability perceptions compare with the effects of other vehicle and infrastructure attributes. This can be helpful, since perceptions of charging infrastructure reliability have not been studied in the literature, but the effect of the other attributes—price, range, charging availability, and operating cost—are known to play a crucial role in the adoption of electric vehicles [23]. Therefore, we can analyze the changes in EV purchase price, EV range, public charging availability, and gasoline price that are equivalent to the change in EV utility generated by a reduction in perceived reliability.

Our structural model results (Table 2) show the control group's perception of reliability is 1.32 units higher than that of the low treatment group. If reliability perceptions were to worsen from the average of the control group to that of the low treatment group, it could significantly impact EV purchasing decisions.

To evaluate the equivalent change, we first calculated the change in utility for the difference in the perceived reliability, R, as shown in Eq. 6.

$$\Delta U_{\Delta R} = \theta \times \Delta R \tag{6}$$

where $\Delta U_{\Delta R}$ is the change in utility associated with a ΔR change in perceived reliability between the control group and the low reliability treatment group. θ is the the estimated coefficient of perceived reliability for respondents without home charging. The equation with the values from Table 2 is shown in Eq. 7

$$\Delta U_{\Delta R} = 0.737 \times -1.32 = -0.973 \tag{7}$$

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

$$\Delta X = \frac{\Delta U_{\Delta R}}{\beta} \tag{8}$$

Table 3: 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
Difference Between Control and Low Treatment Group	- 1.32 units of perceived reliability
EV Price	+ 32% increase on purchase price
Gasoline Price for a Vehicle with 30 mpg Fuel Economy	- $3.86/gallon
Public Charging Station Availability[3]	- 32,571 stations
EV Range	- 366 miles of range

The values presented in Table 3 underscore the influence of poor reliability perceptions on the evaluation of EVs in vehicle purchasing decisions. The decreased perceptions are equivalent to a 32% increase in purchase price. While the price premium of EVs is decreasing, high purchase prices are still consistently a barrier to adoption [40]. This equivalent increase in purchase price underscores that heightened awareness of charging reliability issues could be a similar or greater deterrent to potential EV buyers.

On the other hand, the lower operating cost of EVs compared to conventional vehicles is increasingly compelling for potential buyers [11], [41]. If the cost of gasoline were to decrease by $3.86/gallon, we would expect far fewer to consider purchasing an EV; the same applies if reliability perceptions were to shift to the current conditions.

Additionally, a lack of access to public charging stations remains a barrier to EV adoption [10]. Losing 32,571 stations would reduce the number of public DCFC stations in the U.S. by over 200% [42].

Finally, 366 miles of range is close to the average range of a new EV [43]. Range has consistently been identified as a critical factor in the adoption of alternative fuel vehicles [20], [23], [25], [27], [28], [44], and such a loss in range would significantly impact EV adoption prospects.

Another way to interpret these results is to consider the equivalent changes as what is needed to offset poor charging reliability. In other words, if inconsistent reliability conditions persist and people's perceptions of public charging reliability align more closely with the low treatment group's conditions, we would need a 32% decrease in purchase price, a 366-mile range increase, 32,571 additional public charging stations, and a $3.86/gallon increase in the cost of gasoline to counteract the effect of poor reliability on the willingness to purchase an EV. These comparisons help contextualize how decreasing perceptions of reliability translate into tangible impacts.

On the other hand, improved reliability perceptions 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 comparable to decreasing the purchase price of an EV by 32%. Furthermore, the difference in reliability perceptions between the control group and the high reliability group is equivalent to a 21% reduction in purchase price or an additional 238 miles of EV range. A change in reliability perceptions of this magnitude could significantly increase willingness to adopt EVs.

5 Conclusions and Implications

Our analysis demonstrates the critical influence of public charging station reliability on the willingness to adopt an EV. While billions of dollars of federal funding are dedicated to developing public charging infrastructure [45], access to public charging alone is not sufficient. Unreliable chargers fail to address the fundamental need for EV charging and can lead to serious issues during long-distance travel or for users without access to home charging [46]. If EV infrastructure investments aim to spur higher EV adoption, they should not merely focus on increasing the number of public charging stations but also prioritize improving their reliability.

The establishment of the ChargeX consortium signifies one step toward improving charging reliability and the overall charging experience [47]. There are also promising industry developments in improving reliability across the US. For example, the Tesla Supercharger network, which has better public charging satisfaction among its customers [10], is now accessible to many other vehicle providers [48]. Non-Tesla owners report higher satisfaction when using the Tesla Supercharger network compared with other DCFC chargers [49]. This could make EVs more appealing to consumers.

However, if poor reliability charging experiences impact enough users or public sentiment on charging reliability shifts in the negative direction, we can expect a significant decrease in EV market shares. This

[3] This is based on an estimate that there are approximately 150,000 gas stations in the U.S. [39]

awareness could deter buyers who are otherwise inclined towards EVs. Consequently, unless poor charging experiences with public charging infrastructure are minimized, the transition away from gasoline vehicles could decelerate, impairing our ability to reduce transportation emissions.

As the market continues to move beyond early adopters, we can expect increased resistance to EV adoption. While early EV owners were primarily motivated by environmental concerns, this motivation is already beginning to wane [11]. The next wave of adopters is likely to be less forgiving of the challenges associated with early technology [29]. As we progress beyond early adopters, the overall resistance to purchasing EVs will grow, making reliability issues more pressing.

This study does not identify strategies for changing reliability perceptions. In particular, it does not establish the relationship between the objective and subjective measures of reliability which is critical for defining performance standards that minimize the negative impact of unreliable charging on EV adoption. Future research should examine this relationship by evaluating how varying levels of objective reliability influence perceived reliability.

Additionally, this study focuses on non-EV owners as they represent the next set of EV adopters, and are likely to be less tolerant of charging challenges than early adopters have been [50]. However, existing EV owners have real-world charging experiences which may impact their long-term vehicle retention and continued EV use. Investigating how reliability perceptions change over time among owners, and their effect on EV retention, would be helpful.

Advancements in real-time charging infrastructure data could present an opportunity to study these issues. Access to high-resolution data at spatial and temporal scales could facilitate observational research that isolates the effects of charging reliability on adoption, moving beyond hypothetical stated choice experiments. However, such analyses must account for endogeneity concerns due to the multidirectional relationships among reliability, station utilization, and adoption behavior.

In addition to enabling improved measurement, real-time data may also offer a path to mitigating reliability concerns. If drivers have access to accurate up-to-date charger availability information, the reduction in uncertainty during their travels might improve their perceptions of reliability even if objective reliability measures of individual stations remain unchanged. Future research should explore how real-time data on charger functionality impacts consumer perceptions of reliability as improved planning may mitigate some of the consequences of unreliable public charging.

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.

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References

[1] M. Rika, "US EV Market Passed the 1 Million Sales Mark in 2023," *Statzon*, Mar. 06, 2024. Accessed: May 11, 2024. [Online]. Available: https://statzon.com/insights/us-ev-market

[2] CARB, "States that have Adopted California's Vehicle Regulations," California Air Resources Board. Accessed: May 11, 2024. [Online]. Available: 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

[3] F. Alanazi, "Electric Vehicles: Benefits, Challenges, and Potential Solutions for Widespread Adaptation," *Applied Sciences*, vol. 13, no. 10, Art. no. 10, Jan. 2023, doi: 10.3390/app13106016.

[4] A. Pamidimukkala, S. Kermanshachi, J. M. Rosenberger, and G. Hladik, "Barriers and motivators to the adoption of electric vehicles: A global review," *Green Energy and Intelligent Transportation*, vol. 3, no. 2, p. 100153, Apr. 2024, doi: 10.1016/j.geits.2024.100153.

[5] F. Egnér and L. Trosvik, “Electric vehicle adoption in Sweden and the impact of local policy instruments,” *Energy Policy*, vol. 121, pp. 584–596, Oct. 2018, doi: 10.1016/j.enpol.2018.06.040.
[6] A. C. Mersky, F. Sprei, C. Samaras, and Q. (Sean) Zhen, “Effectiveness of incentives on electric vehicle adoption in Norway - ScienceDirect,” *Transportation Research Part D: Transport and Environment*, vol. 46, pp. 56–68, 2016.
[7] M. Okoma, “The impact of Electric Vehicle Charging Stations on Light Duty Electric Vehicle adoption and rebates California.,” presented at the EVS36, Sacramento, CA, 2023.
[8] W. Sierzchula, S. Bakker, K. Maat, and B. van Wee, “The influence of financial incentives and other socio-economic factors on electric vehicle adoption,” *Energy Policy*, vol. 68, pp. 183–194, May 2014, doi: 10.1016/j.enpol.2014.01.043.
[9] The White House, “FACT SHEET: Biden-Harris Administration Announces New Standards and Major Progress for a Made-in-America National Network of Electric Vehicle Chargers,” The White House. Accessed: Jun. 29, 2024. [Online]. Available: https://www.whitehouse.gov/briefing-room/statements-releases/2023/02/15/fact-sheet-biden-harris-administration-announces-new-standards-and-major-progress-for-a-made-in-america-national-network-of-electric-vehicle-chargers/
[10] R. Singh, D. Malarkey, and D. MacKenzie, “A Review of the Customer Experience at Public Charging Stations and its Effects on Electric Vehicle Purchase and Use,” *Findings*, Sep. 2024, doi: 10.32866/001c.122904.
[11] Plug In America, “2023 EV Driver Survey,” Los Angeles, CA, 2023. [Online]. Available: https://pluginamerica.org/survey/2023-ev-driver-survey/
[12] P. Dvorak, “The Valley of Fire is no place to be when your EV is out of power,” *The Washington Post*, 2023. Accessed: Aug. 14, 2023. [Online]. Available: https://www.washingtonpost.com/dc-md-va/2023/07/31/electric-vehicle-anxiety-logistics/
[13] MotorTrend, “Road-Tripping in Our Long-Term EV Test Cars Has Been … Interesting,” MotorTrend. Accessed: Sep. 18, 2023. [Online]. Available: https://www.motortrend.com/reviews/road-tripping-in-our-long-term-electric-test-cars/
[14] R. Wolfe, “I rented an electric car for a 4-day road trip. I spent more time charging it than I did sleeping.,” Fox Business. Accessed: Sep. 18, 2023. [Online]. Available: https://www.foxbusiness.com/lifestyle/electric-car-four-day-trip-more-time-charging-sleeping
[15] Joint Office of Energy and Transportation, “Biden-Harris Administration to Invest $100 Million for EV Charger Reliability · Joint Office of Energy and Transportation.” Accessed: Sep. 28, 2023. [Online]. Available: https://driveelectric.gov/news/ev-reliability-funding-opportunity
[16] Federal Highway Administration, “National Electric Vehicle Infrastructure Standards and Requirements.” Federal Register, Feb. 28, 2023. Accessed: Nov. 05, 2024. [Online]. Available: https://www.federalregister.gov/documents/2023/02/28/2023-03500/national-electric-vehicle-infrastructure-standards-and-requirements
[17] D. Keith and J. Womack, “Building and sustaining reliable public EV charging in the United States,” *Environmental Research Letters*, vol. 18, no. 1, p. 011004, Jan. 2023, doi: 10.1088/1748-9326/acae39.
[18] D. Rempel, C. Cullen, M. M. Bryan, and G. V. Cezar, “Reliability of Open Public Electric Vehicle Direct Current Fast Chargers,” Apr. 07, 2022, *Rochester, NY*: 4077554. doi: 10.2139/ssrn.4077554.
[19] G. Tal, T. Gamage, V. Karanam, and D. Garas, “Evaluate Zero-Emissions Vehicle Charging Stations at Caltrans Facilities-A Corridor DC Fast Charger Infrastructure Performance Study (Final Report for Agreement 65A0730),” 2023, Accessed: May 15, 2024. [Online]. Available: https://escholarship.org/content/qt0z69n0x6/qt0z69n0x6.pdf
[20] C. R. Forsythe, K. T. Gillingham, J. J. Michalek, and K. S. Whitefoot, “Technology advancement is driving electric vehicle adoption,” *Proceedings of the National Academy of Sciences*, vol. 120, no. 23, p. e2219396120, Jun. 2023, doi: 10.1073/pnas.2219396120.
[21] T. Franke and J. F. Krems, “Understanding charging behaviour of electric vehicle users,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 21, pp. 75–89, Nov. 2013, doi: 10.1016/j.trf.2013.09.002.
[22] A. Jenn, K. Springel, and A. R. Gopal, “Effectiveness of electric vehicle incentives in the United States,” *Energy Policy*, vol. 119, pp. 349–356, Aug. 2018.
[23] F. Liao, E. Molin, and B. van Wee, “Consumer preferences for electric vehicles: a literature review,” *Transport Reviews*, vol. 37, no. 3, pp. 252–275, 2017.
[24] L. Pan, E. Yao, and D. MacKenzie, “Modeling EV charging choice considering risk attitudes and attribute non-attendance,” *Transportation Research Part C: Emerging Technologies*, vol. 102, pp. 60–72, May 2019, doi: 10.1016/j.trc.2019.03.007.
[25] L. Qian and D. Soopramanien, “Heterogeneous consumer preferences for alternative fuel cars in China,” *Transportation Research Part D: Transport and Environment*, vol. 16, no. 8, pp. 607–613, Dec. 2011, doi: 10.1016/j.trd.2011.08.005.
[26] F. Sprei and W. Kempton, “Mental models guide electric vehicle charging,” *Energy*, vol. 292, p. 130430, Apr. 2024, doi: 10.1016/j.energy.2024.130430.
[27] M. Tanaka, T. Ida, K. Murakami, and L. Friedman, “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*, vol. 70, pp. 194–209, Dec. 2014, doi: 10.1016/j.tra.2014.10.019.
[28] E. Valeri and R. Danielis, “Simulating the market penetration of cars with alternative fuelpowertrain technologies in Italy,” *Transport Policy*, vol. 37, pp. 44–56, Jan. 2015, doi: 10.1016/j.tranpol.2014.10.003.
[29] K. Kurani and J. M. Ogunmayin, “How Electric Vehicle Drivers Navigate the Real and Virtual Worlds of Vehicle Charging,” presented at the EVS36 Symposium, Sacramento, CA, 2023.
[30] T. D. Gamage, A. T. Jenn, and G. Tal, “Novel Methodology to Measure the Reliability of Public DC Fast Charging Stations,” *Transportation Research Record*, p. 03611981241244798, Jul. 2024, doi: 10.1177/03611981241244798.
[31] A. J. Miller and N.-K. Nguyen, “Algorithm AS 295: A Fedorov Exchange Algorithm for D-Optimal Design,” *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, vol. 43, no. 4, pp. 669–677, 1994, doi: 10.2307/2986264.
[32] Dynata, “Dynata Global Panel Book,” 2024. Accessed: May 15, 2024. [Online]. Available:

https://www.dynata.com/market-researcher-solutions/global-audiences/
[33] U.S. Census Bureau, "American Community Survey 5-Year Data (2009-2022)," Census.gov. Accessed: Jun. 03, 2024. [Online]. Available: https://www.census.gov/data/developers/data-sets/acs-5year.html
[34] U.S. Census Bureau, "DP04: Selected Housing Characteristics - Census Bureau Table." Accessed: Jun. 03, 2024. [Online]. Available: https://data.census.gov/table/ACSDP1Y2022.DP04?q=home%20ownership
[35] Cox Automotive, "Used-Vehicle Supply and Average Listing Price Declined in January," Cox Automotive Inc. Accessed: Jun. 03, 2024. [Online]. Available: https://www.coxautoinc.com/market-insights/used-vehicle-inventory-january-2024/
[36] Kelley Blue Book, "New-Vehicle Average Transaction Prices Drop to Lowest Level in nearly Two Years, According to Latest Kelley Blue Book Estimates," Kelley Blue Book | MediaRoom. Accessed: Jun. 03, 2024. [Online]. Available: 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
[37] J. Angrist and J.-S. Pischke, "IV and Causality," in *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton University Press, 2008.
[38] A. Vij and J. L. Walker, "How, when and why integrated choice and latent variable models are latently useful," *Transportation Research Part B: Methodological*, vol. 90, pp. 192–217, Aug. 2016, doi: 10.1016/j.trb.2016.04.021.
[39] NACS, "U.S. Convenience Store Count." Accessed: May 14, 2024. [Online]. Available: https://www.convenience.org/Research/Convenience-Store-Fast-Facts-and-Stats/FactSheets/IndustryStoreCount
[40] S&P Global Mobility, "Affordability tops charging and range concerns in slowing EV demand," IHS Markit. Accessed: Jun. 26, 2024. [Online]. Available: https://www.spglobal.com/mobility/en/research-analysis/affordability-tops-charging-and-range-concerns-in-slowing-ev-d.html
[41] D. Malarkey, R. Singh, and D. MacKenzie, "Customer Experience at Public Charging Stations and Its Effects on the Purchase and Use of Electric Vehicles," U.S. Department of Energy, Sep. 2023. Accessed: Jan. 14, 2024. [Online]. Available: https://inl.gov/content/uploads/2023/07/Customer-Experience-at-Public-Charging-Stations_INLRPT-23-74951_12-12-23_Optimized-1.pdf
[42] U.S. Department of Energy, "Alternative Fueling Station Counts by State," Alternative Fuels Data Center. Accessed: May 14, 2024. [Online]. Available: https://afdc.energy.gov/stations/states
[43] Electric Vehicle Database, "Range of full electric vehicles," EV Database. Accessed: Nov. 06, 2024. [Online]. Available: https://ev-database.org/cheatsheet/range-electric-car
[44] T. Zou, M. Khaloei, and D. MacKenzie, "Effects of Charging Infrastructure Characteristics on Electric Vehicle Preferences of New and Used Car Buyers in the United States," *Transportation Research Record*, vol. 2674, no. 12, pp. 165–175, Dec. 2020, doi: 10.1177/0361198120952792.
[45] Federal Highway Administration, "5-year National Electric Vehicle Infrastructure Funding by State |." Accessed: Jun. 26, 2024. [Online]. Available: https://www.fhwa.dot.gov/bipartisan-infrastructure-law/evs_5year_nevi_funding_by_state.cfm
[46] V. Karanam and G. Tal, "How Disruptive are Unreliable Electric Vehicle Chargers? Empirically Evaluating the Impact of Charger Reliability on Driver Experience," Mar. 2023, doi: 10.21203/rs.3.rs-2592351/v1.
[47] Joint Office of Energy and Transportation, "National Charging Experience Consortium · Joint Office of Energy and Transportation," Joint Office of Energy and Transportation. Accessed: Nov. 06, 2024. [Online]. Available: https://driveelectric.gov/chargex-consortium
[48] "Which Electric Vehicles Can Charge at a Tesla Supercharger?," Consumer Reports. Accessed: Nov. 14, 2024. [Online]. Available: https://www.consumerreports.org/cars/hybrids-evs/tesla-superchargers-open-to-other-evs-what-to-know-a9262067544/
[49] J.D. Power, "2024 U.S. Electric Vehicle Experience (EVX) Public Charging Study." Accessed: Nov. 13, 2024. [Online]. Available: https://www.jdpower.com/business/press-releases/2024-us-electric-vehicle-experience-evx-public-charging-study
[50] E. M. Rogers, A. Singhal, and M. M. Quinlan, "Diffusion of Innovations," in *An Integrated Approach to Communication Theory and Research*, 2nd ed., Routledge, 2008.

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