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ELECTRIC VEHICLE ADOPTION AND USE IN RURAL AND URBAN UTAH

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Final Report
April 2026

RESEARCH

Keeping Utah Moving
Utah Department of Transportation - Research Division
4501 South 2700 West - P.O. Box 148410 - SLC,UT 84114-8410

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<tr><td colspan="4">16. Abstract
This research project sought to better understand factors affecting electric vehicle (EV) adoption, use, and charging behaviors in Utah, and any differences between urban and rural areas. To accomplish this goal, three key datasets were used: Utah's 2023 household travel survey, 2015–2024 Utah vehicle registrations by county, and a 2021–2023 survey of "gig" drivers (who work for ridehailing and delivery companies) about EVs. Several key outcomes were studied: EV registrations, household vehicle ownership and EV adoption, daily travel behaviors, charging behaviors, and gig driver EV perceptions and preferences. Following literature reviews and statistical analyses, the research team identified explanatory factors and differences in EV adoption, use, and charging behavior between urban and rural parts of Utah. EV adoption in Utah is increasing among registered vehicles, especially in rural areas and for light trucks. Utah travel survey data analysis indicated relatively few differences in the factors influencing the travel behaviors of EV-owning and non-EV households. Instead, EV-specific travel and charging behavior results suggest that rural EV users (residents and visitors) are more strategic about their use and charging of EVs, whereas urban EV users can be more opportunistic. These findings suggest that public EV charging is important, especially in rural areas. Analysis of gig driver surveys found Salt Lake City to have lower EV adoption than other cities in the western US, suggesting needs around EV leasing options, targeted marketing, and public EV charging in urban areas, to help facilitate electrification of the gig driving sector.</td></tr>
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UNIT CONVERSION FACTORS

SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. (Adapted from FHWA report template, Revised March 2003)

LIST OF ACRONYMS

ASPIRE	Advancing Self-Sufficiency through Powered Infrastructure for Roadway Electrification
BEV	Battery electric vehicle
CFA	Confirmatory factor analysis
CFI	Comparative Fit Index
DCFC	Direct current fast charger
EDU	Economic disutility
EFA	Exploratory factor analysis
EV	Electric vehicle
EVCI	Electric vehicle charging infrastructure
EVSE	Electric vehicle supply equipment
FHWA	Federal Highway Administration
GIS	Geographic information systems
GPH	Gas-powered or plug-in hybrid electric vehicles
HH	Household
HTS	Household travel survey
ICEV	Internal combustion engine vehicle
IRR	Incidence rate ratio
LL	Log-likelihood
MAG	Mountainland Association of Governments
MPO	Metropolitan planning organization
OR	Odds ratio
PDU	Personal disutility
PHEV	Plug-in hybrid electric vehicle
RMP	Rocky Mountain Power
RMSEA	Root Mean Square Error of Approximation
SEM	Structural equation modeling
SoC	State of charge
SRMR	Standardized Root Mean Residual

TLI	Tucker-Lewis Index
UDOT	Utah Department of Transportation
WFRC	Wasatch Front Regional Council

EXECUTIVE SUMMARY

The goal of this research project was to understand factors affecting electric vehicle (EV) adoption, use, and charging behaviors in Utah, and any differences between urban and rural areas. To accomplish this goal, the research team utilized three different key datasets: Utah's 2023 household travel survey, ten years (2015–2024) of Utah vehicle registrations by county, and a 2021–2023 survey of "gig" drivers (who work for ridehailing and delivery companies) about EVs. Several key outcomes were studied: EV registration rates, household vehicle ownership, household EV adoption, household- and vehicle-level daily travel behaviors, trip- and household/day-level charging behaviors, and EV perceptions and preferences from gig drivers. Following a literature review and various statistical analyses, the research team identified factors associated with these outcomes, as well as differences in EV adoption, use, and charging behavior between more urban and more rural areas of Utah, measured as within versus outside of the Wasatch Front region. The report closes with a summary of key findings about EVs and transportation electrification in Utah, as well as recommendations for implementation.

The first analysis investigated trends in EV registrations in Utah (by county and vehicle class) through logistic models of EV adoption rates. As of 2024, EVs—battery-electric (BEV), plug-in hybrid (PHEV), and standard hybrid EVs—were a larger share of passenger cars (5.6%) than light trucks (3.8%); however, light trucks are electrifying more rapidly. If current trends continue, by 2050 (26 years from 2024) around half of all registered vehicles in Utah will be EVs. Although urban areas have higher rates of EV adoption, rural areas of Utah are experiencing rapid EV growth, especially for BEVs and light trucks.

The second analysis used 2023 Utah household travel survey data to study household vehicle ownership and EV adoption (BEV or BEV/PHEV). Higher household income, more educational attainment, and owning a home were household characteristics associated with greater EV adoption. Results around vehicle ownership suggested that EVs are often secondary vehicles for urban (but not rural) households. Accessibility to public EV charging infrastructure had a modest role, suggesting that improved charging infrastructure could impact vehicle electrification, if expanded. Overall, the factors influencing EV adoption remained largely the same across urban/rural contexts, suggesting that there may be similar motivations for having an EV for urban and rural households, at least among early adopters.

The third analysis used similar Utah travel data to investigate daily household and vehicle travel behaviors—including no travel, trip frequency, distance, and duration—comparing EVs versus non-EVs (for BEVs only, and BEVs or PHEVs) and urban vs. rural households. Household structure (workers, students, children), income, and vehicle availability strongly shaped travel participation and intensity. Although EV-owning households did not exhibit differences in travel outcomes compared to non-EV households, EVs themselves were less likely to not be used on a given day, and they made more daily trips, at least in urban areas. Additionally, some regional contrasts were evident, especially around income effects. Overall, the findings suggest that EV ownership itself does not substantially alter daily travel patterns once household and demographic characteristics are considered, but spatial context amplifies socioeconomic differences in mobility.

The fourth analysis used Utah travel survey data for BEVs/PHEVs to analyze three charging behavior outcomes: the presence of a charger at a trip's destination, choosing to charge at the end of a trip, and household choosing to charge at home at the end of the day. Results showed that although home destinations were the most likely to have EV charging infrastructure present, charging at the end of a trip was actually more likely at work and other non-home destinations. Rural destinations visited by EV users were more likely to have a charger, and EV users in rural areas were more likely to charge at their destination, which highlights the importance and desirability of public charging for rural EV-owning households and for EV users traveling to and through rural areas. The positive association between distance traveled and both charger presence and charging behavior for rural (but not urban) trips, suggests that rural EV users rely more on strategic charging, while urban EV users rely more on opportunity charging.

The fifth analysis studied whether gig drivers in four western US cities (including Salt Lake City) used BEVs, were likely to prefer BEVs, and inquired about their EV-related beliefs. The analysis highlighted a strong relationship between perceptions of the lifestyle compatibility of EVs and intended future BEV adoption. Perceptions that EVs would be personally challenging to use seemed to outweigh economic concerns around cost, range, and battery life.

1.0 INTRODUCTION

1.1 Problem Statement

The shift toward sustainable transportation, with electric vehicles (EVs) as a central element, is vital for reducing air pollution, improving health, and stabilizing transportation costs. Air quality is a pressing concern in Utah, heightened by the state's unique geography, including dry, mountainous topography, which contributes to elevated levels of particulate matter and ozone. These air quality issues are unfortunately common (in different ways) to both urban and rural areas. Therefore, it is important to facilitate the adoption and use of EVs in both urban and rural areas of Utah, to ensure all populations receive the benefits of transportation electrification. This is also an urgent issue, as UDOT needs to make decisions about siting EV charging stations throughout the state. Fortunately, the recent 2023 Utah Moves Transportation (Household Travel) Survey offers rich data that can be analyzed for understanding EV adoption and use in rural and urban Utah.

Differences in the adoption and use of EVs in urban and rural areas—as influenced by personal, social, and infrastructural factors—needs more study in order to develop effective strategies and guide EV charging infrastructure (EVCI) investments to support the growing consumer adoption of EVs. Studies show that factors like age, gender, education, and income greatly influence the decision to buy and use EVs. Social influences, such as political views, peer pressure, environmental awareness, and government policies, are also crucial. Collectively, these factors affect how attractive EVs are to potential users, especially in rural areas where transportation needs and social norms can be quite different from those in cities. Additionally, research shows that EV users generally make shorter trips under 10 miles and charge their vehicles overnight, fitting within EV range limits. EV charging habits are shaped by factors like vehicle features, user preferences, charging infrastructure availability, and environmental consciousness. However, the lack of nearby public charging stations in rural areas with lower population densities is a potential challenge to adoption/use. Also, many parts of rural Utah see seasonally high tourist activities (visiting state and national parks and other recreation areas), involving longer-distance travel and higher peak charging demands. Therefore, advances in EV ranges and expanded public charging networks are essential to meet especially rural travel needs and promote wider EV adoption.

In summary, this research is crucial for understanding differences in EV adoption, use, and charging behaviors in urban and especially rural areas of Utah.

1.2 Objectives

The overall goal of this research project was **to understand factors affecting electric vehicle (EV) adoption, use, and charging behaviors in Utah, and any differences between urban and rural areas**. This goal was accomplished through several more specific objectives:

- Identify factors affecting the **household adoption of EVs**, including any differences in urban and rural areas of Utah.
  - This includes studying EV adoption in specific markets, such as among ridehail and delivery drivers who work in the "gig" economy.
- Identify factors affecting the **use of EVs** as compared to non-EVs (travel behaviors of EV and non-EV users), including any differences in urban and rural areas of Utah.
- Identify factors affecting the **charging behaviors of EV users**, including any differences in urban and rural areas of Utah.

1.3 Scope

To accomplish these objectives, the research team undertook several linked and coordinated tasks. First, the entire scope of the research project was split into five distinct components for more efficient execution. (See Chapters 2.0 through 6.0 for details.) Within each of these sub-projects, the research team completed the work through several steps:

- *Literature review*: Conducted a concise but comprehensive review of existing literature. Focused on differences between urban and rural areas. Identified knowledge gaps in current research and opportunities for innovation.
- *Data assembly*: Assembled data on EV adoption, use, and charging behaviors from a variety of sources, including:

- *Utah Moves Transportation Survey*: Utah's latest household travel survey, collected in 2023 using a combination of online surveys and app-based data collection, includes detailed travel behaviors linked to personal and household characteristics. Information on EV ownership, vehicle use, and charging behavior were available.
    - *Utah Vehicle Registrations*: Yearly data (2015–2024) on electric/hybrid vehicle registrations is available, by vehicle type, for all counties and zip codes in Utah.
    - *Other available datasets*: Other datasets specific to Utah or the Intermountain West on EV adoption and perceptions were available for use in this project. Specifically, the "Western Smart EV at Scale" project (Rocky Mountain Power, funded by the US Department of Energy) collected survey and charging episode data in 2021–2023 from EV users who did "gig" work for Uber, Lyft, DoorDash, and other passenger/food delivery companies.
- *Data analyses*: Analyzed the assembled data to provide insights, using statistical methods and models such as: log-linear regression, logistic regression, Poisson regression, negative binomial regression, exploratory and confirmatory factor analysis, and structural equation modeling. Compared groups (EV vs. non-EV, urban vs. rural) using interactions and segmented models.
- *Results and discussion*: Summarized and discussed results of each of the analyses, in light of the literature and the objectives. Provided recommendations and implementation opportunities. Prepared final deliverables.

1.4 Outline of Report

This report contains the following chapters:

1. **Introduction**: Summarizes the problem, overarching research objective(s), and general approach. *Authors*: Patrick Singleton & Fariba Soltani Mandolakani.
2. **Electric Vehicle Adoption Trends in Utah**: Describes trends in EV registrations in Utah and estimates adoption models to predict future EV registration growth by type and location. *Authors*: Aleks Paskett & Patrick Singleton.

3. **Electric Vehicle Adoption in Urban and Rural Utah**: Studies factors associated with household vehicle ownership and EV adoption and compares these relationships among urban and rural households in Utah. *Authors*: Fariba Soltani Mandolakani & Patrick Singleton.
4. **EV Travel Behavior in Urban and Rural Utah**: Studies factors associated with daily travel behaviors (didn't travel, trip frequency, distance, and duration) for households and for vehicles in Utah, and compares EV and non-EV households, EVs and non-EVs, and urban and rural households. *Authors*: Fariba Soltani Mandolakani & Patrick Singleton.
5. **Charging Behaviors of EV Users in Urban and Rural Utah**: Studies factors associated with charging behaviors (destination has a charger, charged at the trip end, and charged at home at end-of-day) for EV users in Utah, and compares urban and rural households and trips. *Authors*: Aleks Paskett & Patrick Singleton.
6. **Identifying Key Factors for "Gig Driver" Electrification**: Analyzes current vehicle type choice, EV-related beliefs, and vehicle preferences for EVs among "gig" drivers (working for ridehailing or delivery companies) in four US cities, including Salt Lake City. *Authors*: William Bouck & Patrick Singleton.
7. **Conclusions**: Summarizes key findings, discusses limitations, presents recommendations, and describes an implementation plan. *Author*: Patrick Singleton.

When reviewing the chapters, it is important to note that they each use slightly different definitions of an "EV" and distinctions between different types of EVs: battery-only (BEV), plug-in hybrid (PHEV), and standard hybrid EVs. Chapter 2.0 investigates registration trends in BEV, PHEV, and standard hybrid EVs separately and in various combinations. Chapters 3.0 and 4.0 study the adoption and use of EVs in two ways: BEVs only, and BEVs or PHEVs. Chapter 5.0 combines BEVs and PHEVs together when analyzing EV charging behaviors. Chapter 6.0 focuses on BEVs separately from gas-powered or hybrid EVs (GPHs). These differences are important to consider when interpreting the results and findings.

<u>2.0 ELECTRIC VEHICLE ADOPTION TRENDS IN UTAH</u>

2.1 Abstract

The transportation sector is undergoing a major transformation as electric vehicles (EVs) increasingly replace internal combustion engine vehicles. Understanding where and how quickly EV adoption is taking place is critical for effective infrastructure planning, especially around EV supply equipment and EV charging infrastructure such as public charging stations. Without clear forecasts of EV adoption, state and local planners may risk under- or over-investing in charging infrastructure, particularly in areas that may be experiencing unexpected growth rates for their population densities. This study uses vehicle registration data from the Utah State Tax Commission to summarize EV registrations throughout the State of Utah and utilizes a logistic adoption model to estimate future adoption based on current trends. Based on the results of this modeling process, if current adoption trends continue, half of all registered vehicles in Utah will be EVs of any type (battery, plug-in hybrid, or standard hybrid) in approximately 26 years. As a vehicle class, light trucks have a more rapid adoption of EVs, and the current trend shows that half of Utah light trucks will be EVs in just under 14 years. Rural areas in Utah are experiencing rapid EV growth, especially for light trucks. Based on the results of the modeling process, it is expected that a significant proportion of vehicles in these areas will be battery-only EVs within the next 20 years. These results will help to inform planners of target areas for EV infrastructure development.

2.2 Introduction

The transportation sector is undergoing a major transformation as *electric vehicles (EVs)* increasingly replace internal combustion engine vehicles (ICEVs). There are a variety of fuel type options for EVs, including *standard hybrids* (that run on gas, but also have an electric motor), *plug-in hybrids* (that run on a battery that can be plugged in to charge, but can also run on gas), and fully electric or *battery electric vehicles (BEVs)* (that only run on a battery and plug in to charge).

Driven by environmental concerns, operational cost savings, and technological advancements, the rate of EV adoption has accelerated dramatically in recent years. However, the pace and pattern of adoption vary substantially across vehicle types, fuel types, and geographies, presenting unique challenges for planning agencies. EV adoption in Utah has grown at an increasing rate over the last ten years. Figure 2.1 shows the total number of EVs, as well as individual EV types, registered each year in the state from 2015 to 2024.

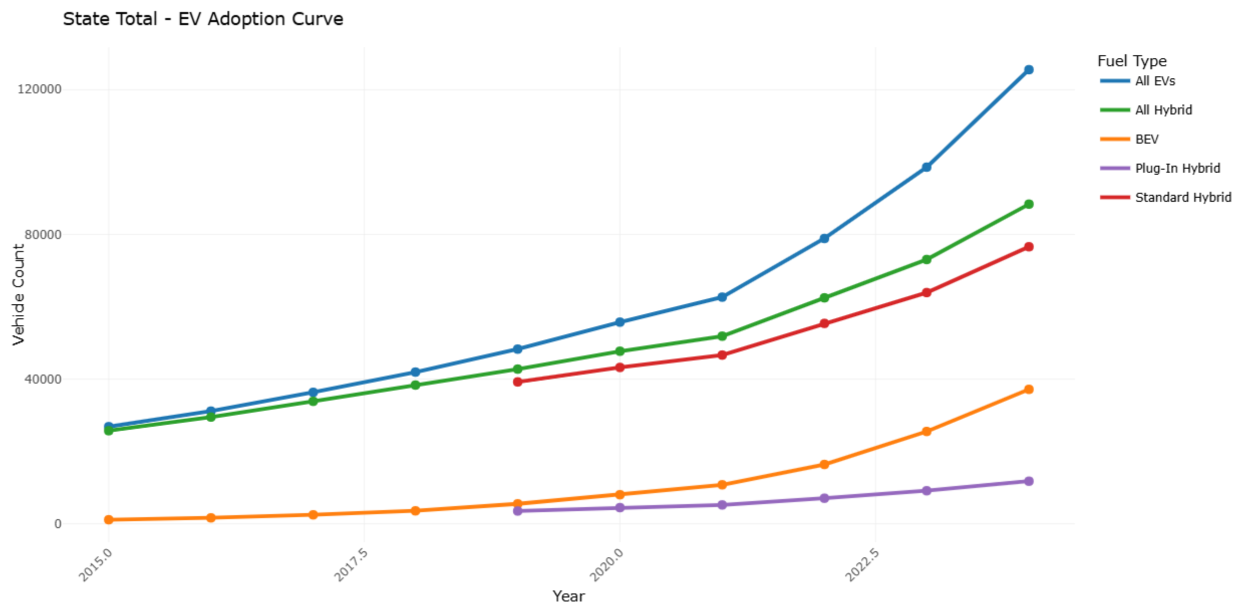

Figure 2.1: EV Registrations by type from 2015 to 2024

Notes: All EVs = All Hybrid + BEV. All Hybrid = Standard Hybrid + Plug-In Hybrid.

Understanding where and how quickly EV adoption is taking place is critical for effective infrastructure planning, especially around EV supply equipment (EVSE) and EV charging infrastructure (EVCI) such as public charging stations. Without clear forecasts of EV adoption, state and local planners may risk under- or over-investing in charging infrastructure, particularly in areas that may be experiencing unexpected growth rates for their population densities.

This report models electric vehicle adoption trends in the State of Utah using up to ten years of vehicle registration data. We apply a logistic growth model consistent with methods from the academic literature (Sinton et al., 2024) to estimate the current rate and projected timing of EV market saturation. The approach is based on fitting a two-parameter logistic curve to observed penetration data at the county level, for different vehicle types (e.g., passenger vehicles, light trucks) and fuel types (e.g., standard hybrid, plug-in hybrid, battery electric). By analyzing both state-level and county-level trends, this work identifies high and low-growth areas, highlighting disparities that could affect infrastructure needs. This report will help UDOT identify priority areas for the implementation of EV-supporting infrastructure, thus meeting the evolving needs of Utah's traveling public.

2.3 Data and Methods

2.3.1 Data

Vehicle registration data for 2015 through 2024 were collected from the website of the Utah State Tax Commission (Utah State Tax Commission, n.d.). These files provide information on vehicle registrations in Utah each year and contain several tables for different registration types and geographies. For this project, only the data for on-highway vehicle registrations by county, vehicle type, and fuel type were analyzed. The data were cleaned and formatted to allow for easier modeling and analysis.

Due to variations in the formatting and reporting of the data in each year, some assumptions had to be made in preparing and combining the data for analysis. Most of these were simple adjustments to spelling; however, some categories of vehicle and fuel types were not reported every year. At varying times, counties stopped reporting "Passenger – Standard" and "Passenger – Low Speed" as different vehicle types. As the combined count of these two categories is consistent with the counts for just "Passenger – Standard" after the discontinuation, it is assumed that these two categories can be safely combined into one "Passenger" category to standardize the dataset. Additionally, starting in 2019, plug-in hybrids began to be reported as a separate category from all other hybrids. Therefore, the model includes one "All Hybrids" category, modeled across all ten years, and separate "Standard Hybrids" and "Plug-in Hybrids" categories, modeled only since 2019.

After the multi-year registration data were aligned and combined into a single file, some additional categories were created before modeling. First, a total of "All Vehicles" of a given fuel type per county was created by summing the counts for "Heavy Trucks," "Light Trucks," "Passenger Vehicles," and "Motorcycles" of each fuel type. Next, a total of "All Electric Vehicles" for each vehicle type (including the new "All Vehicles" category) was created by summing the counts for "BEVs," "Plug-In Hybrid," and "Standard Hybrid" vehicles for each year. Finally, the "All Hybrids" category was created by summing the "Standard Hybrid" and "Plug-In Hybrid" counts. After these new counts were created, the EV percentage for each category was calculated as the total count of a given vehicle and fuel type divided by the total number of vehicles in that geography for that year. For example, in 2024, Morgan County had 66 electric passenger vehicles out of a total of 5,185 passenger vehicles, resulting in an adoption rate of 1.27% for electric passenger vehicles.

In a final step, several new geographies were constructed by grouping existing counties. Utah has many counties with small populations, so to help address potential modeling issues, some counties with low numbers of vehicles (less than 20,000 total vehicle registrations as of 2024) were combined into county groups. These groups were chosen based on neighboring counties, either grouping a small county with a larger neighboring county or grouping three small counties together. The county groupings, as well as the total number of vehicles, the total number of EVs, and the percentage of EVs—using data from 2024—is shown in Table 2.1.

Table 2.1: Utah county groups, total vehicles, total EVs, and percentage of EVs

County group	*All vehicles*	*All EVs*	*% EVs*
State of Utah	2,942,473	125,550	4.3%
Summit, Wasatch	104,688	5,459	5.2%
Utah	507,164	25,920	5.1%
Salt Lake	999,927	50,740	5.1%
Davis	291,017	14,001	4.8%
Washington, Kane	217,700	9,057	4.2%
Cache, Rich	115,051	4,109	3.6%
Weber, Morgan	238,039	7,885	3.3%
Iron	60,899	1,506	2.5%
Tooele	83,172	1,966	2.4%
Box Elder	68,613	1,520	2.2%
Garfield, San Juan, Wayne	23,651	391	1.7%
Carbon, Emery, Grand	51,323	786	1.5%
Sanpete, Sevier, Piute	65,680	929	1.4%
Juab, Millard, Beaver	44,424	625	1.4%
Duchesne, Uintah, Daggett	71,125	656	0.9%

2.3.2 Methods

To estimate EV adoption curves for forecasting, logistic adoption models were estimated. Such S-shaped logistic curves are commonly used to model the adoption of new technologies (Kros, 2005; Meija et al., 2024). We model the EV adoption rate (EV proportion of registered vehicles) y for a given geography (county group) i as a function of time (years since 2019) t:

$$y_i(t) = \frac{s}{1+\exp(-a_i - b_i t)} \qquad \text{(Eq. 1)}$$

where a_i affects the horizontal shift of the curve, b_i defines the growth rate, and s is the final market saturation proportion. In practical terms, a more negative value for a_i indicates EV adoption began earlier or higher, and a larger value of b_i indicates a faster rate of change in adoption over time. Final saturation s is on a scale of 0 to 1, with 1 representing 100% penetration, meaning we assume that all vehicles in the geography will eventually be of the fuel type being modeled. From the estimated model's parameters, the time from $t = 0$ (2019) to reach half of market penetration h_i can be calculated as the ratio of a_i and b_i as follows:

$$h_i = \frac{-a_i}{b_i} \qquad \text{(Eq. 2)}$$

To capture a full picture of EV adoption in Utah, several models were estimated to reflect different vehicle types, fuel types, and market saturations. These models were analyzed for the state of Utah as a whole and each county (group) individually. For each geography, a different model was created for each combination of vehicle type, fuel type, and s-value. Vehicle types included "All" (which encompassed all registered vehicles), passenger vehicles, and light trucks. Motorcycles and heavy trucks were not given individual models due to low numbers in these classes, making modeling infeasible. EV fuel types included BEVs, plug-in hybrids, standard hybrids (not plug-in), all hybrids (standard hybrid + plug-in hybrid), and all EVs (BEVs + all hybrids). The s-values modeled included 1.00, 0.75, 0.50, and 0.25. This is consistent with the scenarios found in the literature (Sinton et al., 2024), which reflect unknown future targets of EV market saturation.

Once the modeling process was developed and proven successful, a web-based application (Paskett & Singleton, 2025) was created using R, to help with visualizing and interpreting the results. This web application allows the user to plot EV registrations from 2015 to 2024, see model results for any combination of the scenarios described above, and map EV registrations and adoption in the state of Utah. Figure 2.2 presents an example of the mapping tool, showing the percentage of EVs in each county in 2024. This app can be accessed at https://ap98.shinyapps.io/UT-EV-Adoption-app/.

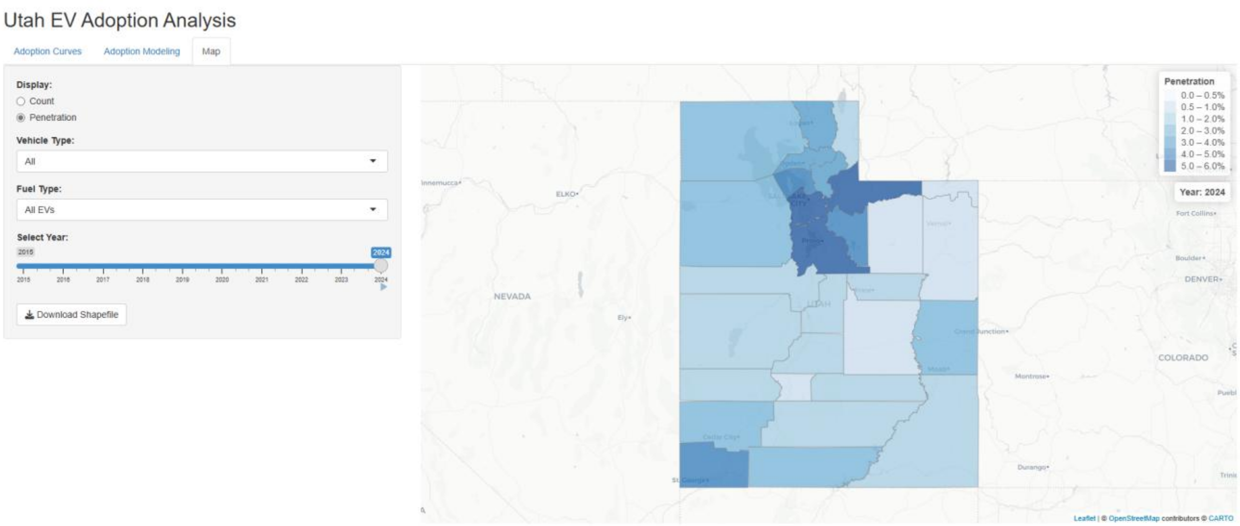

Figure 2.2: Example of the map tool included in the web app

2.4 Results

This section provides some highlighted results from the different modeling scenarios, such as fast-growing counties, vehicle classes, or specific EV types. For brevity, the full model results are not included in this report but may be accessed using the web tool linked above. Note that the model results are contingent on the aggregate factors and trends influencing EV adoption remaining steady or continuing to change at their current rates. Adoption of a specific vehicle class, EV type, or in a specific area may increase or decrease based on advances in technology, policy adjustments, economic changes, or other changes in market trends.

2.4.1 Statewide Results

Statewide analysis shows that EV adoption is progressing in Utah, but notable differences exist between different vehicle classes and specific EV types. Although EVs currently (as of 2024) make up a higher percentage of passenger vehicles (5.6%) than light trucks (3.8%), light trucks are consistently the fastest growing vehicle class of EVs. Based on the modeled trends, light trucks are expected to reach 50% EV market penetration within approximately 14 years (from 2019). By contrast, the statewide percentage of all EVs is projected to reach 50% in approximately 26 years. The results for statewide modeling of all types of EVs are shown in Table 2.2.

Table 2.2: Statewide modeling results for all EV types

Vehicle type	*s*	*a*	*b*	*h*
All	1.00	-3.94	0.15	25.65
	0.75	-3.65	0.15	23.54
	0.50	-3.23	0.16	20.50
	0.25	-2.49	0.17	15.04
Passenger	1.00	-3.45	0.12	27.99
	0.75	-3.15	0.12	25.24
	0.50	-2.75	0.13	21.24
	0.25	-1.95	0.14	14.05
Light truck	1.00	-5.08	0.37	13.73
	0.75	-4.79	0.37	12.87
	0.50	-4.38	0.38	11.62
	0.25	-3.69	0.39	9.39

Some significant differences were also shown between individual types of EVs. BEVs displayed a higher growth rate than both types of hybrids, while standard hybrids had the slowest growth rate of the three types. This suggests a market shift toward fully electric vehicles, possibly driven by advancements in BEV technology and supporting charging infrastructure. Additionally, when modeling for BEVs specifically rather than all EV types, the statewide adoption rate increases. In this scenario, light trucks are expected to reach 50% penetration in just over 12 years, with 50% adoption across all vehicles in under 17 years. By comparison, plug-in hybrids are expected to reach 50% adoption across all vehicles in approximately 47 years, and standard hybrids in approximately 28 years. Across all fuel types, light trucks remain the fastest-growing vehicle class. The model results for the 100% adoption scenario ($s = 1$) of BEVs, plug-in hybrids, and standard hybrids are shown in Table 2.3.

Table 2.3: Comparison of models for BEVs, plug-in hybrids, and standard hybrids

Vehicle type	*s*	*a*	*b*	*h*
BEV				
All	1.00	-6.21	0.37	16.79
Passenger	1.00	-5.57	0.30	18.77
Light truck	1.00	-7.53	0.62	12.20
Plug-in hybrid				
All	1.00	-6.19	0.22	27.61
Passenger	1.00	-5.71	0.13	44.67
Light truck	1.00	-6.91	0.47	14.72
Standard hybrid				
All	1.00	-4.13	0.09	46.83
Passenger	1.00	-3.66	0.07	54.13
Light truck	1.00	-5.17	0.28	18.21

2.4.2 Results by County

Modeling counties individually (or in groups) gives insights into areas of the state with leading or lagging EV adoption. Across all types of vehicles (Table 2.4), Summit and Wasatch counties have the highest growth rate and are projected to reach 50% adoption in approximately 21 years (from 2019), 5 years ahead of the statewide average. Davis and Utah counties are the second and third fastest growing, respectively. Despite its early high adoption, EV registrations in Salt Lake County are increasing at about the same rate as the entire state. The Carbon, Emery, and Grand County group is the slowest growing area of the state, expected to reach 50% adoption in approximately 47 years, 21 years after the statewide average. For BEVs only, the counties with the highest starting levels (Summit, Wasatch, and Salt Lake) are increasing at a rate slightly slower than the statewide average. Instead, more rural counties with lower EV adoption levels are increasing faster, at least according to current trends. For BEVs specifically, the grouping of Juab, Millard, and Beaver counties show the fastest growth rate of all county groups. However, Utah and Davis counties are projected to be the first to reach 50% BEV saturation, in around 15–16 years.

Table 2.4: Model results for county groups for all vehicle types

Fuel type	*County group*	*s*	*a*	*b*	*h*
All EVs	**State of Utah**	1.00	-3.94	0.15	25.65
	Summit, Wasatch	1.00	-3.87	0.19	20.88
	Davis	1.00	-3.93	0.18	22.40
	Utah	1.00	-3.82	0.17	22.53
	Salt Lake	1.00	-3.74	0.15	25.31
	Weber, Morgan	1.00	-4.26	0.16	26.09
	Cache, Rich	1.00	-4.11	0.15	26.86
	Iron	1.00	-4.49	0.16	28.51
	Washington, Kane	1.00	-3.83	0.13	30.21
	Box Elder	1.00	-4.56	0.14	31.50
	Tooele	1.00	-4.43	0.14	32.04
	Sanpete, Sevier, Piute	1.00	-5.04	0.15	33.40
	Duchesne, Uintah, Daggett	1.00	-5.56	0.16	33.73
	Garfield, San Juan, Wayne	1.00	-4.85	0.13	36.06
	Juab, Millard, Beaver	1.00	-4.92	0.12	40.24
	Carbon, Emery, Grand	1.00	-4.72	0.10	47.31
BEVs	**State of Utah**	1.00	-6.21	0.37	16.79
	Utah	1.00	-6.11	0.41	15.03
	Davis	1.00	-6.29	0.41	15.32
	Summit, Wasatch	1.00	-5.49	0.36	15.36
	Salt Lake	1.00	-5.84	0.35	16.87
	Weber, Morgan	1.00	-6.81	0.40	17.06
	Washington, Kane	1.00	-6.60	0.38	17.43
	Juab, Millard, Beaver	1.00	-8.76	0.48	18.35
	Tooele	1.00	-7.25	0.39	18.43
	Iron	1.00	-7.66	0.41	18.72
	Box Elder	1.00	-7.70	0.41	18.73
	Cache, Rich	1.00	-6.77	0.36	18.91
	Carbon, Emery, Grand	1.00	-8.42	0.44	19.27
	Sanpete, Sevier, Piute	1.00	-8.37	0.42	19.90
	Duchesne, Uintah, Daggett	1.00	-8.77	0.42	20.67
	Garfield, San Juan, Wayne	1.00	-8.29	0.40	20.68

Looking specifically at light trucks (Table 2.5) (which include pickup trucks, SUVs, and minivans), the core urban counties of Utah (Davis, Salt Lake, Utah) are projected to reach 50% EV saturation slightly faster than the statewide average, in approximately 12–13 years. However, adoption rates are relatively high across the state, even in rural counties with low current levels of EV light truck adoption. In particular, the groupings of Duchesne, Uintah, and Daggett Counties and Garfield, San Juan, and Wayne Counties are tied for the fastest growth rate, for all types of EVs. Again, for BEVs only, the Juab, Millard, and Beaver County group has the fastest growth rate for BEV light trucks of all county groups.

Table 2.5: Model results for county groups for light trucks only

Fuel type	*County group*	*s*	*a*	*b*	*h*
All EVs	**State of Utah**	1.00	-5.08	0.37	13.73
	Utah	1.00	-5.04	0.40	12.66
	Davis	1.00	-5.07	0.40	12.81
	Salt Lake	1.00	-4.78	0.36	13.38
	Summit, Wasatch	1.00	-4.45	0.32	13.86
	Weber, Morgan	1.00	-5.39	0.39	13.98
	Washington, Kane	1.00	-5.20	0.37	14.22
	Cache, Rich	1.00	-5.23	0.36	14.50
	Iron	1.00	-5.98	0.39	15.17
	Tooele	1.00	-6.03	0.39	15.62
	Garfield, San Juan, Wayne	1.00	-6.56	0.42	15.76
	Box Elder	1.00	-5.98	0.36	16.47
	Duchesne, Uintah, Daggett	1.00	-6.96	0.42	16.71
	Juab, Millard, Beaver	1.00	-6.85	0.40	17.18
	Sanpete, Sevier, Piute	1.00	-6.59	0.38	17.41
	Carbon, Emery, Grand	1.00	-6.24	0.34	18.12
BEVs	**State of Utah**	1.00	-7.53	0.62	12.20
	Davis	1.00	-7.76	0.69	11.30
	Utah	1.00	-7.29	0.63	11.59
	Salt Lake	1.00	-7.26	0.62	11.73
	Weber, Morgan	1.00	-8.18	0.66	12.46
	Summit, Wasatch	1.00	-6.24	0.50	12.52
	Cache, Rich	1.00	-8.34	0.64	12.96
	Washington, Kane	1.00	-7.74	0.57	13.57
	Juab, Millard, Beaver	1.00	-11.01	0.80	13.79
	Sanpete, Sevier, Piute	1.00	-10.28	0.73	14.01
	Tooele	1.00	-8.69	0.62	14.02
	Box Elder	1.00	-9.18	0.65	14.16
	Duchesne, Uintah, Daggett	1.00	-11.08	0.78	14.27
	Iron	1.00	-8.96	0.61	14.73
	Carbon, Emery, Grand	1.00	-9.47	0.62	15.31
	Garfield, San Juan, Wayne	1.00	-9.64	0.60	16.04

2.5 Conclusions

Rural areas in Utah are experiencing rapid EV growth, especially for light trucks. Based on the results of the modeling process, it is expected that a significant proportion of vehicles in these areas will be BEVs within the next 20 years. While Park City and urban Utah counties currently have higher levels of EV adoption than rural Utah, many rural counties have higher changes in adoption rates, especially for BEVs and light trucks. In the scenario assuming eventual 100% adoption of BEVs, the last county group to reach 50% penetration will be Garfield, San Juan, and Wayne Counties in approximately 21 years (for all vehicle classes) or 16 years (for light trucks) from 2019, which is 2035–2040. The Utah Department of Transportation

(UDOT) should work to evaluate the public EV charging capacity in these rural counties and ensure there is enough capacity to handle the increased demand from these vehicles.

It should also be noted that these forecasts only focus on the counties where vehicles are registered, not necessarily where they are driven. For example, EV charging stations in many rural Utah counties would need to be sized and located to accommodate not just local traffic but also visitors from urban Utah or other states who may be visiting national or state parks or other recreational destinations. Overall, these results suggest a rapid adoption of EVs across the state of Utah over the next 20 years, showing a need for timely and targeted EV charging infrastructure development.

2.6 References

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3.0 ELECTRIC VEHICLE ADOPTION IN URBAN AND RURAL UTAH

3.1 Abstract

Electric vehicle (EV) adoption is a crucial step toward achieving Utah's climate and sustainability goals, especially given the state's growing population, severe air quality challenges, and upcoming global events such as the 2034 Winter Olympics. This study uses data from the 2023 Utah Moves Household Travel Survey and a spatial accessibility/proximity analysis to examine how household characteristics and access to public charging infrastructure influence vehicle ownership and EV adoption across urban and rural contexts in Utah. Key independent variables include household income, size, and composition, education level, residential type and tenure, and proximity to public EV charging infrastructure. We employ a series of Poisson and binary logistic weighted regression models to analyze vehicle ownership and the likelihood of battery EV or plug-in hybrid EV adoption, including differences in urban and rural areas. Household income is a consistent and significant predictor across all models (and regions), playing a central role in both vehicle ownership and EV adoption. Education and housing tenure also predict EV adoption: College-educated households and homeowners are more likely to have EVs. The number of household vehicles is positively associated with EV adoption in urban areas but not rural areas, suggesting EVs are often secondary vehicles for urban households. Accessibility to public EV charging infrastructure has a modest but positive association overall, suggesting that improved charging infrastructure could impact vehicle electrification, if expanded. The findings underscore the importance of place-based, context-sensitive strategies and infrastructure investments to support the transition to EVs.

3.2 Introduction

Electric vehicles (EVs) are a vital component of the transition toward sustainable transportation, offering substantial environmental benefits by eliminating tailpipe emissions and reducing reliance on non-renewable fossil fuels. Increasing EV adoption is crucial to national and regional planning efforts aimed at reducing emissions from petroleum refining, transportation, and combustion. This need is especially acute in Utah, where unique geographic and climatic conditions lead to significant air quality challenges. For instance, the Wasatch Front in northern Utah regularly experiences winter inversion events that trap pollutants, resulting in some of the worst air quality in the US (Flowerday et al., 2023). These conditions are exacerbated by high concentrations of particulate matter and ozone layer in the state's dry, mountainous basins. Hosting the 2034 Winter Olympics (IOC, n.d.) will further increase trip generation during a time of year already plagued by poor air quality, intensifying the need for cleaner mobility options. Expanding EV adoption before the Games could help mitigate the environmental and health impacts of these events, benefiting both residents and the anticipated influx of visitors.

Utah's population grew by around 7% from 2020 to 2024 driving increased travel demand and vehicle ownership, especially in a car-dependent state with limited rural transit. Tourism to national parks and recreation areas adds to vehicle emissions. Expanding electric vehicle charging infrastructure (EVCI), particularly in rural areas, is key to maintaining clean air and meeting public demand. Despite these needs, EV adoption rates vary widely across different groups and areas. Like any new technology, EVs face differential uptake influenced by a combination of socio-demographic, economic, psychological, and policy-related factors (Bindhya et al., 2025; Rahman et al., 2025; Khader et al., 2025). Another factor central to adoption decisions is the proximity and availability of charging infrastructure, both at home and in public (Egue & Long, 2012; Soltani Mandolakani & Singleton, 2024; Arias-Gaviria et al., 2021). Moreover, built environment characteristics such as density, land use, and proximity to amenities can also significantly influence adoption, yet these have received limited attention in EV studies (Sheng et al., 2025; Laviolette, 2023). Research shows that rural areas in the US are adopting EVs at a lower rate (40% lower) than urban areas, despite accounting for a majority (70%) of road miles (Heintz, 2023). Spatial and economic disparities (Ding & Wu, 2025) further illustrate that even within urban settings, lower per capita charger availability in dense areas can hinder adoption.

In this report, we seek to examine patterns of EV adoption across urban and rural areas in Utah. Specifically, we explore how socio-economic characteristics, spatial factors, and spatial proximity to public charging stations affect EV adoption rates. Using regression analysis, we aim to quantify the influence of these variables and identify critical barriers and enablers, especially factors having differing influences in urban versus rural areas. The findings of this research will provide valuable insights for planners, policymakers, and utility providers in designing localized strategies to expand EV adoption and improve charging infrastructure. As Utah moves toward a future shaped by growth, global visibility, and increasing environmental pressures, understanding these dynamics is crucial to meeting the demands on the state's transportation system.

3.3 Literature Review

EV adoption is shaped by a variety of factors including economic, demographic, infrastructural, geographic, and psychological influences. These factors manifest differently in urban and rural contexts, making it essential to understand their roles to promote adoption throughout the states. Nevertheless, few studies have explicitly compared how these factors operate across urban and rural areas within the US, leaving important geographic differences in EV adoption underexplored.

One of the most consistent barriers to EV adoption is the lack of accessible, reliable, and affordable charging. Kumar and Alok (2020) identified range anxiety, cost, and limited availability of charging stations as primary concerns among consumers. Azadfar et al. (2015) also emphasize that the availability, location, and type of charging stations directly affect EV usage. For many, at-home charging is not a viable solution due to housing type or cost; thus, public EV charging is an important resource.

In urban settings, proximity to public EVCI varies (Tyler & Clawson, 2023). Qian et al. (2025) found better proximity to public chargers in lower-income and minority neighborhoods, due to their closeness to major roads and public spaces. On the other hand, Tomás and Marqués (2023) showed that population density negatively affects per capita charger availability, resulting in poorer accessibility to EVCI for communities living in high-density areas. Sheng et al. (2025) highlight the role of urban design and land use in shaping spatial proximity of EV chargers. While these studies provide valuable insights into urban charging accessibility, few have examined how such spatial and infrastructural patterns differ in rural environments, where public charging opportunities are typically more dispersed.

In rural areas, these challenges to EV adoption may be more pronounced. Heintz (2023) reports that EV adoption rates in rural communities are significantly lower than in urban areas. Jones et al. (2020) demonstrated that small rural businesses were more willing to adopt EVs when provided with financial support, infrastructure, and technical assistance. Overall, research on rural EV adoption remains relatively limited, especially in understanding how spatial accessibility to EVCI influences adoption, compared to urban areas.

While geographic location (rurality in particular) poses structural and infrastructural barriers to EV adoption, individual-level factors further influence these patterns. Demographics play a significant role in shaping EV adoption. Research shows that younger and higher-income individuals are more likely to adopt EVs (Bindhya et al., 2025; Rahman et al., 2025; Sadeghvaziri et al., 2024); however, gender and education show little influence. Studies also note the relevance of household vehicle ownership in shaping EV adoption, with most EV-owning households being multi-vehicle households rather than single-vehicle households (Bushnell et al., 2022; Zaino et al., 2024). On the other hand, renters, lower-income households, and individuals living in multi-family dwellings without garages often cannot install home charging units (Tyler & Clawson, 2023), and thus they may be less likely to adopt EVs.

Beyond demographic and structural factors, psychological and perceptual considerations also influence EV adoption. Studies show that environmental awareness, perceived benefits, and social influence support adoption, while perceived risks, high upfront costs, and limited range act as barriers (Skipper et al., 2023). Psychological variables such as personal norms, emotional responses, and societal values also affect intention and behavior. Political orientation and environmental consciousness are also influential: Younger, environmentally aware individuals tend to favor EVs; left-leaning individuals emphasize policy and environmental benefits, while right-leaning individuals focus more on financial considerations (Priyam et al., 2024). Although these subjective influences on EV adoption can be difficult to measure, they may be associated with various demographic characteristics such as age or education that are more easily measurable.

Individual motivations do not occur in isolation; they are also shaped by the accessibility of charging infrastructure. Consumers in areas with EV policy support and visible infrastructure are more likely to adopt (Singh et al., 2020; Priessner et al., 2018). Reliable and fast public charging, as well as local government backing, are increasingly necessary to shift consumer behavior. Neves et al. (2019) also argue that consumers now expect affordable and efficient charging networks to support long-term EV use.

Taken together, prior research provides valuable insights across economic, behavioral, and infrastructural dimensions, yet few studies have integrated these perspectives to directly compare EV adoption patterns between urban and rural communities in the US.

3.3.1 Conceptual Framework

Figure 3.1 illustrates a conceptual framework of interrelated factors influencing both household vehicle ownership (as a precondition) and EV adoption. Among these factors, household income stands out as a dominant predictor for both outcomes (Xia et al., 2022; Dargay et al., 2007; Berrill et al., 2024). Higher-income households are more likely able to afford multiple vehicles and manage the upfront costs of EVs, although participation among middle-income groups is also becoming increasingly common (Fujita et al., 2024). Built-environment characteristics significantly influence vehicle ownership (Tao & Næss, 2022). Households located closer to city centers and those with greater accessibility to shops, services, and employment tend to be less reliant on personal vehicles (Skipper et al., 2023; Ding et al., 2018; Sabouri et al., 2021; Zhang et al., 2020). Similarly, neighborhoods with dense populations and high intersection density, which are indicators of walkable environments, are associated with lower car ownership rates (Fujita et al., 2024). Housing-related factors, such as type of residence and feasibility of home charging, play a critical role in shaping EV adoption. Most BEV owners tend to live in single-family homes with reliable access to garages or outdoor outlets, which makes at-home charging practical and convenient (Fujita et al., 2024). These infrastructure advantages, combined with public charging access, further support EV adoption, particularly for households lacking private charging options or commuting longer distances (Kumar & Alok, 2020). Additionally, social and psychological factors such as environmental concern, as well as anticipated travel patterns, directly affect the usability and attractiveness of EVs (Jones et al., 2020). Finally, household vehicle ownership itself directly contributes to EV adoption. Many EV owners come from multi-vehicle households, suggesting that EVs are frequently introduced as secondary or supplementary vehicles (Tyler & Clawson, 2023). This trend reinforces the idea that EV adoption often begins in households that already have the resources and flexibility to test and transition to new vehicle technologies (Fujita et al., 2024).

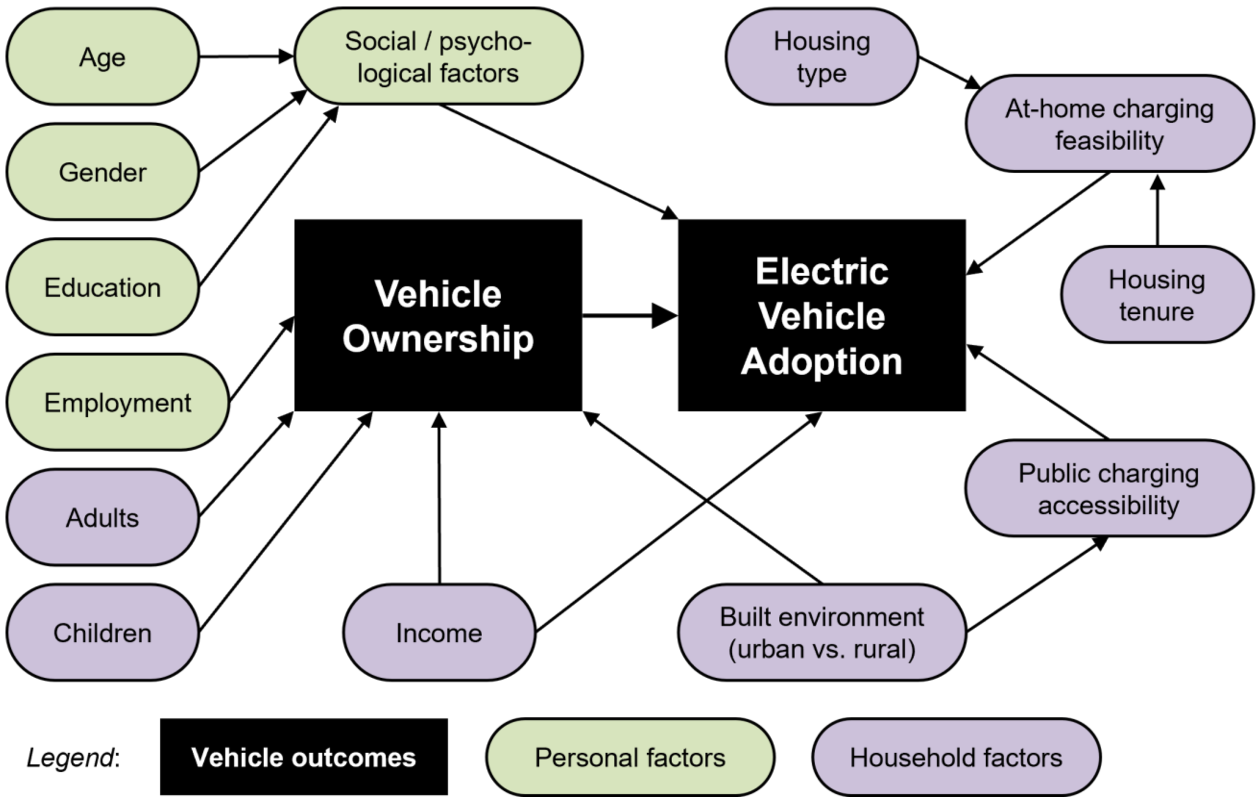

Figure 3.1: Hypothesized factors affecting EV adoption, from the literature

3.4 Methodology

3.4.1 Data Sources

This study primarily utilized data from two sources: first, the 2023 Utah Moves Household Travel Survey Data, obtained from the Wasatch Front Regional Council (WFRC); and second, accessibility to public EV charging stations, calculated for this project by the authors using a GIS-based spatial analysis.

The 2023 Utah Moves Transportation Survey employed a comprehensive, modern approach to collect travel behavior and demographic data from residents across Utah (Utah Unified Transportation Plan, n.d.). The program consisted of three interrelated efforts: a general household travel survey (HTS), a university travel survey, and a follow-on and long-distance survey. The study followed a two-part design: a recruitment survey to gather household demographic information, and a travel diary to capture individual-level travel behavior over a specified period. Data collection modes included smartphone app (rMove), web-based surveys, and telephone interviews, allowing for flexibility and broader participation. This study primarily used the HTS, which gathered detailed information from over 11,000 households between February and June 2023. Relevant for this study, the HTS collected data on household and personal characteristics, including vehicle ownership and the presence of battery electric vehicles (BEVs) or plug-in hybrid electric vehicles (PHEVs).

After cleaning the data, our sample size was 9,479 households. Our analysis is household-based, because vehicle decisions tend to be made through deliberation and input from multiple household members, and vehicles can be shared among household drivers. This means that our independent variables and dependent variables represent the whole household, not individuals in the household. Figure 3.2 presents a refined version of the conceptual framework shown in Figure 3.1; it highlights only those variables available in our dataset, as described earlier, and forms the basis of our empirical analysis. The diagram illustrates both direct and indirect relationships between various factors and both HH vehicle ownership and EV adoption, focusing specifically on the measurable variables used in our models. For instance, social/psychological factors (like environmental values) were not measured in the survey, so education and age are being included as predictors of EV adoption not because we think they directly impact adoption, but rather because they are proxies for the latent psychological variables.

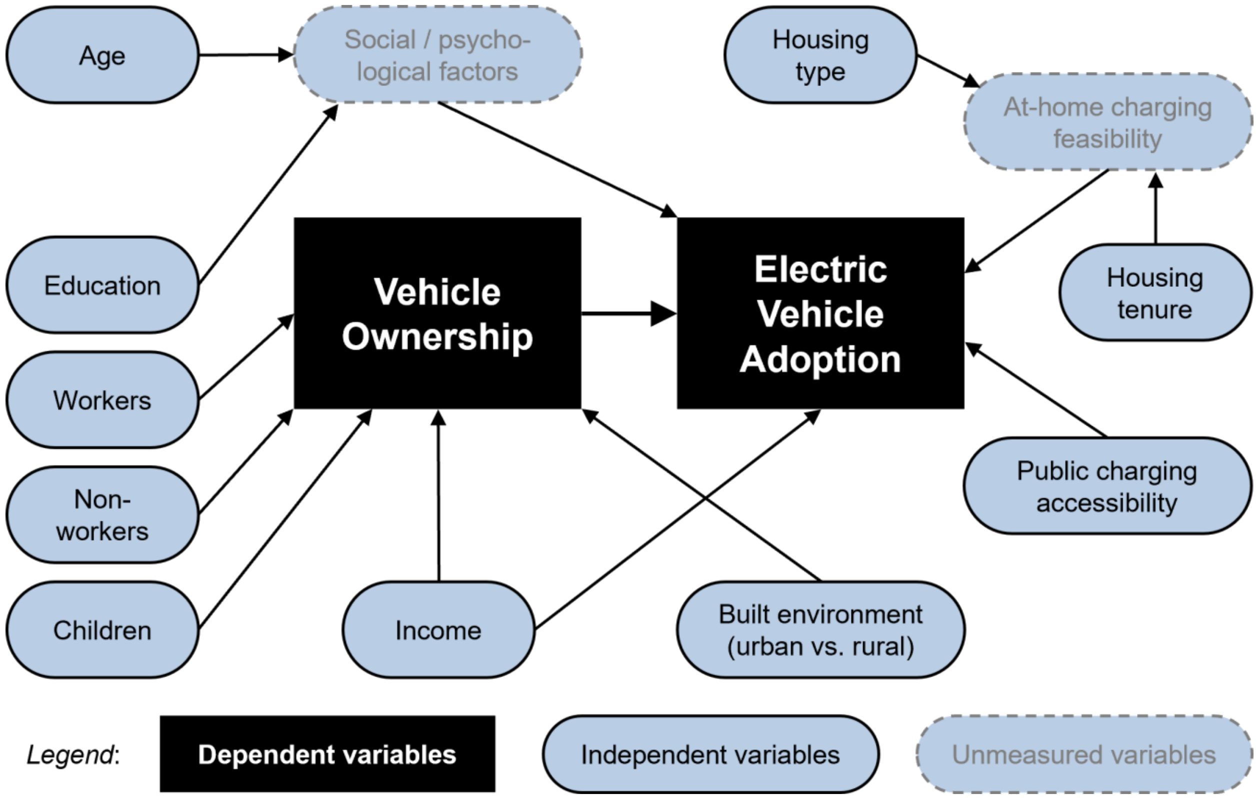

Figure 3.2: Hypothesized factors affecting EV adoption, available from the data

To measure access to public EV charging stations, we conducted a GIS-based spatial accessibility analysis; more information can be found in a paper (in-draft) that is available by contacting the authors. Specifically, ArcGIS Pro was used to calculate an origin-destination (O-D) "cost" matrix. Origins i were defined as the centroids of US Census block groups, while opportunities or destinations j were public EV charging stations located within a 100-mile radius of each block group center. Charging station locations were obtained from the Alternative Fuel Data Center (U.S. Department of Energy, n.d.) and filtered to reflect stations installed at the time of the HTS (Spring 2023). In the O-D analysis, travel times were calculated using ArcGIS road network datasets.

The accessibility (proximity) score for each block group A_i was calculated by applying the following Equation 1, as recommended by Levinson and Wu (2020):

$$A_i = \sum_{j=1}^{J} O_j f(C_{ij}) = \sum_{j=1}^{J} O_j e^{\theta C_{ij}} \quad (1)$$

where the cost function $f(C_{ij})$ is the common exponential function $e^{\theta C_{ij}}$, cost C_{ij} is the GIS-obtained travel time between the origin i (block group centroid) and the destination j (public EV charging station), and parameter $\theta = -0.08$ (0). In essence, accessibility is the number of EV charging stations that are near a given home, weighted by the driving time to reach them (e.g., 50% at 8.7 minutes, 10% at 28.8 minutes, 1% at 57.6 minutes).

Figure 3.3 presents the resulting EV charging accessibility values across the entire state of Utah, while Figure 3.4 provides an enlarged view highlighting accessibility patterns within the Wasatch Front urban corridor.

Table 3.1 summarizes the descriptive statistics for the variables used in the analysis. The dependent variables were the number of household vehicles (an integer or count variable) and whether or not the household has a BEV, or either a BEV or PHEV (both binary true/false variables). Independent variables included the number of adults, children, and workers in the household; the age of the responding adult and the highest education level among household members (proxies for social/psychological factors affecting EV adoption); household income; housing type and tenure (proxies for at-home charging feasibility); accessibility to public EV charging stations; and region. The age variable, although measured in categories on the survey (see footnote to Table 3.1), was included as a continuous variable in the analysis for the sake of simplicity. For the same reason, the multiple types of educational attainment and housing type were collapsed into two categories each: with or without a college degree, and single-family versus multi-family housing. Because around 90% of Utah's population lives within a US Census-defined urban area (Wikipedia, n.d.), we took a coarse and region-based measure of urbanity versus rurality: Households were classified as "urban" if they lived within the Wasatch Front[1] and "rural" if they lived elsewhere in the state (outside of the Wasatch Front).

[1] Technically, we used the metropolitan planning organization (MPO) area boundaries (shown in Figure 4) for the MPOs that represent the Salt Lake City, Provo–Orem, and Ogden–Layton metropolitan areas: the Wasatch Front Regional Council (WFRC), and the Mountainland Association of Governments (MAG). This area captures most of the contiguous urbanized areas along the I-15 corridor. There are other MPOs in Utah (in Cache and Washington Counties), but they represent urban areas (Logan and St. George) that are much smaller and geographically separate from the Wasatch Front region.

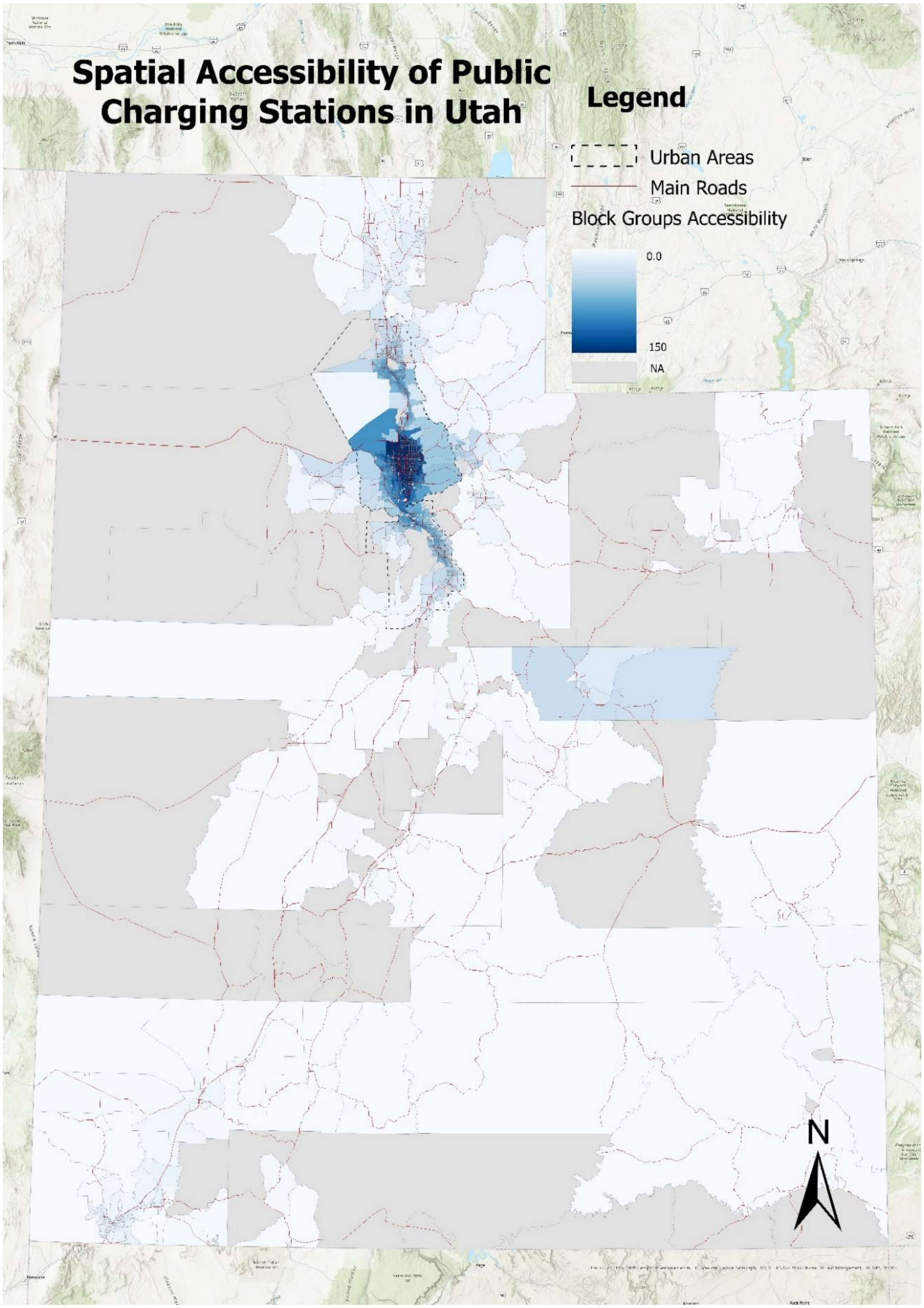

Figure 3.3: Spatial accessibility to public EV charging stations, Utah statewide

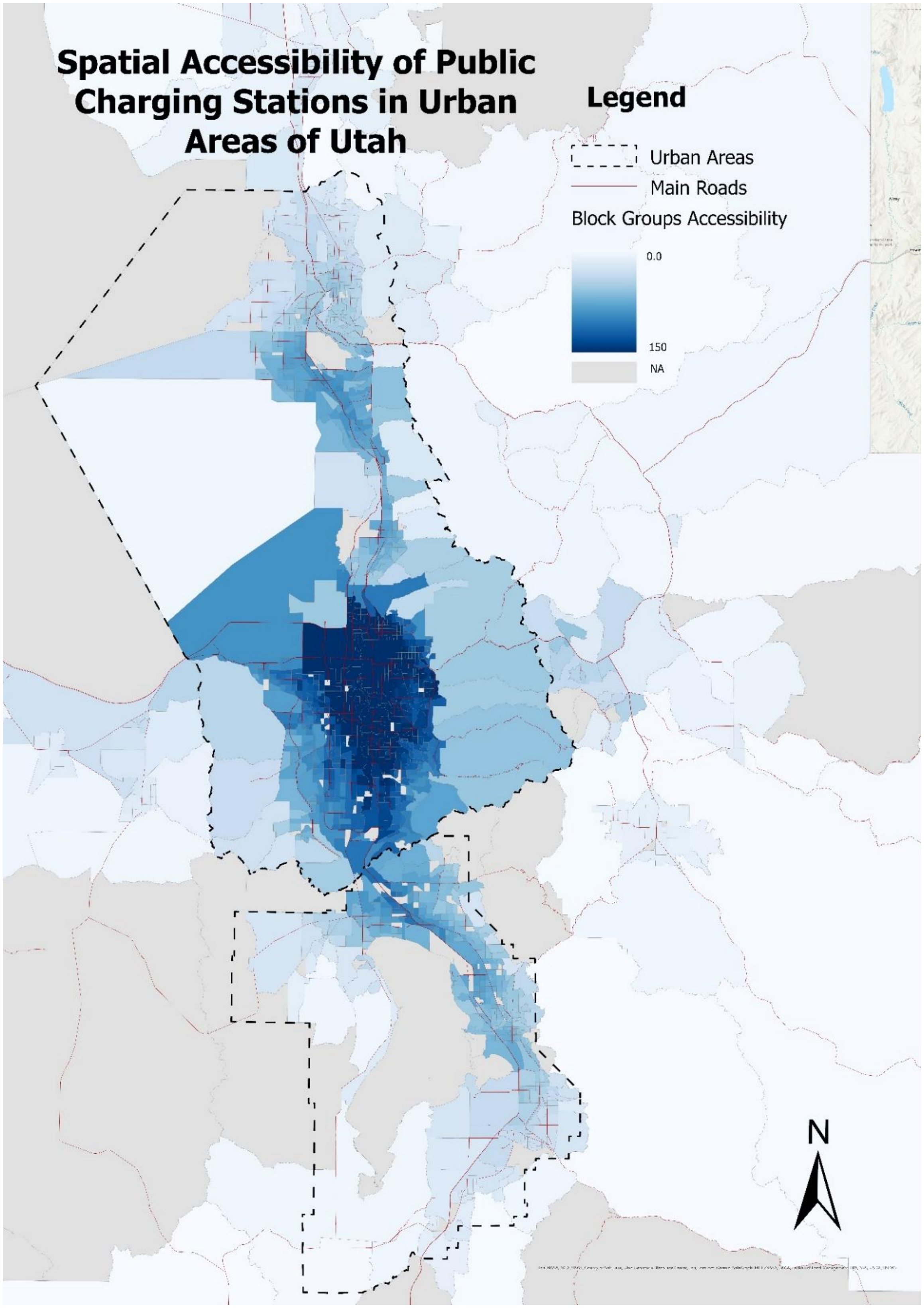

Figure 3.4: Spatial accessibility to public EV charging stations, Wasatch Front

Table 3.1: Descriptive statistics of sample households

Variable	*Categorical variables*		*Continuous variables*		
	#	*%*	*Mean*	*SD*	*Min, Median, Max*
Dependent variables					
Number of household vehicles			1.82	1.08	0, 2, 8
Household has a BEV: True	246	2.60			
False	9,233	97.40			
Household has a BEV/PHEV: True	339	3.58			
False	9,140	96.42			
Independent variables					
Number of workers			1.37	1.08	0, 1, 13
Number of non-workers			0.70	0.83	0, 1 ,7
Number of children (age <18)			0.60	1.13	0, 0, 8
Age of responding adult (categories 1–11[a])			6.58	1.88	4, 6, 11
Highest education level: College degree	6,161	65.00			
No college degree	3,318	35.00			
Household income: Under \$50,000	3,313	34.95			
\$50,000- \$99,999	3,221	33.98			
\$100,000-\$199,999	2,395	25.27			
\$200,000 or more	550	5.80			
Housing type: Single-family	6,549	69.09			
Multi-family	2,930	30.91			
Housing tenure: Own	5,811	61.30			
Rent	3,668	38.70			
Accessibility to public EV charging stations			57.77	44.90	0.00, 48.65, 154.56
Region: Urban (Wasatch Front)	6,616	69.80			
Rural (outside Wasatch Front)	2,863	30.20			

[a] Age categories: 1: under 5, 2: 5–15, 3: 16–17, 4: 18–24, 5: 25–34, 6: 35–44, 7: 45–54, 8: 55–64, 9: 65–74, 10: 75–84, 11: 85 or older.

The dependent variables were slightly different for residents of urban versus rural areas. Households in rural areas owned more vehicles on average than those in urban areas (1.98 vs 1.75 vehicles). At the same time, EV adoption was higher in urban regions: 2.9% of urban households owned at least one all-electric vehicle (BEV), compared with 2.0% in rural areas, and 3.9% versus 2.8% when plug-in hybrids were also counted (BEV/PHEV).

3.4.2 Data Analysis

To evaluate factors influencing household vehicle ownership and EV adoption, and any differences in urban versus rural areas, our analysis involved six regression models, based on the conceptual framework (Figure 3.1) and its empirical operationalization (Figure 3.2). The models are summarized in Figure 3.5, split into two groups.

The first set of models explored factors affecting overall vehicle ownership, as a precursor for EV adoption. Model 1 was a Poisson regression model of the number of household vehicles, selected because of the count data outcome. (Tests of a negative binomial model found no overdispersion, so the simpler Poisson model was used.) Model 2 introduced an interaction of all coefficients with the built environment measure (urban versus rural areas) to explore how these relationships vary geographically, potentially highlighting the influence of location-specific factors. Independent variables in the vehicle ownership Models 1 and 2 were the number of adults, children, and workers, household income, and region.

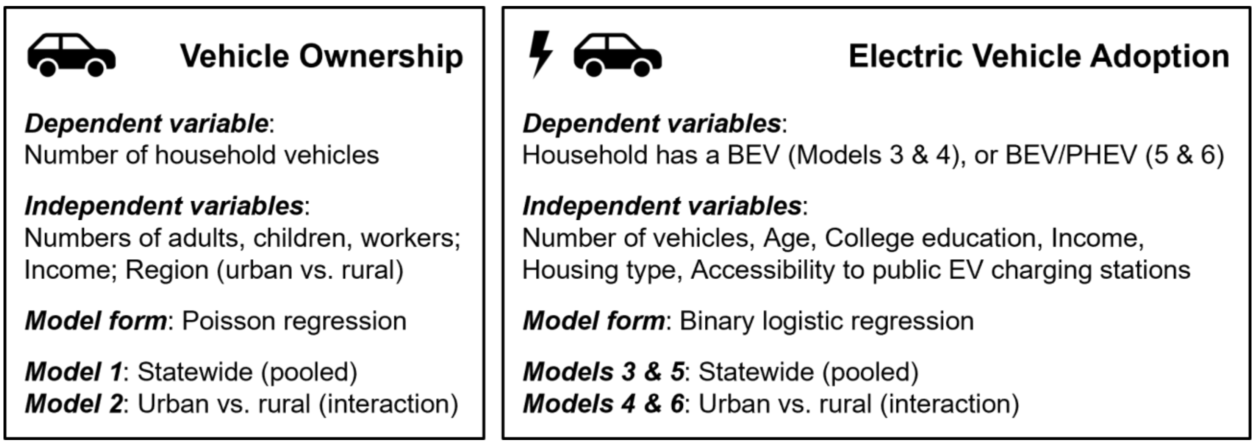

Figure 3.5: Structure of vehicle ownership and EV adoption models

The EV adoption component of the analysis focused on understanding the likelihood of households adopting an EV, either a BEV or a BEV/PHEV, both treated as binary outcomes (true/false). Therefore, Model 3 applied binary logistic regression to whether or not the household had a BEV, with Model 4 incorporating built environment (urban versus rural) interactions. Similarly, Models 5 and 6 assess BEV/PHEV adoption using the same model specification. Independent variables in the EV adoption Models 3–6 were the number of household vehicles, the age of the responding adult, the highest education level, household income, housing type, and accessibility to public EV charging stations. (Accessibility entered in the model as a linear term. We also tried using the natural log of accessibility instead, but the model fit statistics were slightly worse.)

The models were all estimated as weighted regressions, to account for any major sources of non-representativeness in the sample. Household weights were constructed by the survey vendor and provided by WFRC. The weights were created from geographically specific sampling probabilities, adjusted to better match population distributions on household size, household income, number of workers, number of vehicles, and number of children. Because the weights were originally expansion weights (scaled to sum to the regional population), we scaled them to be adjustment weights (scaled to sum to the number of observations in the sample). Most (90%) of the final weights were between 0.07 and 3.56, with a maximum weight of 16.19.

Overall, these models allow for a detailed investigation into how socio-demographic factors (e.g., income, education), residential context (e.g., single- vs. multi-family housing), and access to charging infrastructure influence the decision to adopt cleaner vehicle technologies. (All independent variables were inspected for multicollinearity using pairwise correlations; no large correlations were found, indicating no problematic multicollinearity.) By comparing results across models and geographic contexts, the study provides insights into both the general and place-specific drivers of EV adoption and vehicle ownership.

3.5 Results and Discussion

3.5.1 Household Vehicle Ownership

Table 3.2 presents the results of the Poisson regression Models 1 and 2, estimating the number of household vehicles based on predictors such as number of workers, non-workers, children, household income, and whether or not the household resides in a rural area (outside the Wasatch Front).

Table 3.2: Results of Poisson regression models for household vehicle ownership

Coefficient	*Est.*	*S.E.*	*z*	*p*
		Model 1: Statewide		
Intercept	-0.1822	0.0219	-8.317	<0.001
Number of workers	0.2113	0.0064	32.916	<0.001
Number of non-workers	0.1593	0.0082	19.429	<0.001
Number of children (age <18)	0.0100	0.0055	1.809	0.071
Household income: $50,000-$99,999	0.4407	0.0213	20.695	<0.001
$100,000-$199,999	0.5365	0.0208	25.836	<0.001
$200,000 or more	0.5984	0.0261	22.899	<0.001
Region: Rural (outside Wasatch Front)	0.1684	0.0159	10.609	<0.001
		Model 2a: Urban		
Intercept	-0.2002	0.0253	-7.905	<0.001
Number of workers	0.2280	0.0077	29.699	<0.001
Number of non-workers	0.1627	0.0095	17.053	<0.001
Number of children (age <18)	0.0124	0.0066	1.874	0.061
Household income: $50,000-$99,999	0.4024	0.0260	15.454	<0.001
$100,000-$199,999	0.5205	0.0251	20.768	<0.001
$200,000 or more	0.5911	0.0302	19.565	<0.001
		Model 2b: Rural		
Intercept	0.0390	0.0396	0.983	0.326
Number of workers	0.1740*	0.0123	14.187	<0.001
Number of non-workers	0.1421	0.0163	8.722	<0.001
Number of children (age <18)	0.0065	0.0102	0.636	0.525
Household income: $50,000-$99,999	0.5108*	0.0371	13.768	<0.001
$100,000-$199,999	0.5547	0.0374	14.850	<0.001
$200,000 or more	0.5721	0.0548	10.448	<0.001

Sample size (N = 9,479).
Goodness-of-fit statistics: Null model (LL = -14,921), Model 1 (LL = -13,709, McFadden R^2 = 0.081), Model 2 (LL = -13,696, McFadden R^2 = 0.082).
* Significant difference (p<0.05) for rural vs. urban.

When looking at Utah statewide (Model 1), almost all hypothesized factors were significantly associated with household vehicle ownership ($p < 0.05$). Households with more workers and non-workers tended to own more vehicles. Specifically, the number of workers had the strongest association among the household composition variables (incidence rate ratio (IRR) = $e^{Est.}$ = 1.235), implying that each additional worker would increase the expected number of vehicles by approximately 24%, compared to about 17% for each additional non-working adult. A smaller but still positive (marginally significant) association was found for the number of children (IRR = 1.010). Household income was also an important and strong predictor, with higher income associated with higher vehicle ownership. In fact, households with incomes of $200,000 or more would be expected to have nearly twice as many vehicles (IRR = 1.819) as households with incomes below $50,000. Households located in rural areas owned about 18% more vehicles (IRR = 1.183) than urban households, on average.

The interaction Model 2 separates results for urban and rural households (within versus outside the Wasatch Front). For urban residents (Model 2a), all of the hypothesized factors were still statistically significant, with roughly similar magnitudes. (This is not surprising, since urban residents comprise 70% of the statewide sample.) For rural residents (Model 2b), most of the hypothesized factors were also significant, except that there was no association between vehicle ownership and the number of children (but the best estimate was still positive). When comparing magnitudes of the estimates between urban and rural residents, the associations for workers (IRR_{Urban} = 1.256, IRR_{Rural} = 1.190), non-workers (IRR_{Urban} = 1.177, IRR_{Rural} = 1.153), and children (IRR_{Urban} = 1.013, IRR_{Rural} = 1.006) were all slightly smaller in the rural model, implying that household size factors may play a smaller role in household vehicle ownership in rural areas. However, the difference was only statistically significant ($p < 0.05$) for the number of workers. For income, the impact of households with incomes \$50,000 to \$99,999 (compared to lower income) was stronger in rural areas than urban areas (IRR_{Rural} = 1.667, IRR_{Urban} = 1.495), a statistically significant difference. Nevertheless, in rural areas, income showed more of a plateau effect on vehicle ownership (with a threshold at \$50,000); whereas, in urban areas, vehicle ownership kept increasing with higher income.

3.5.2 Household EV Adoption

Table 3.3 presents the results of six binary logistic regression models examining household EV adoption across the state of Utah. Models 3 and 5 represent the full statewide samples for two definitions of EV ownership: owning at least one BEV and owning either a BEV or PHEV, respectively. Models 4a and 6a focus on urban households, while Models 4b and 6b focus on rural households, providing insight into the geographic differences in EV adoption drivers.

Table 3.3: Results of logistic regression models for household EV adoption

	Household has a BEV				Household has a BEV/PHEV			
Coefficient	***Est.***	***S.E.***	***z***	***p***	***Est.***	***S.E.***	***z***	***p***
	Model 3: Statewide				**Model 5: Statewide**			
Intercept	-5.4785	0.3371	-16.254	<0.001	-4.7906	0.2723	-17.593	<0.001
Number of household vehicles[a]	0.2483	0.0532	4.664	<0.001	0.2438	0.0458	5.319	<0.001
Age of responding adult[b] (categories 1–11)	-0.0673	0.0417	-1.613	0.107	-0.0780	0.0354	-2.207	0.027
Highest education level: College degree	0.6877	0.1841	3.735	<0.001	0.7147	0.1536	4.653	<0.001
Household income: $50,000-$99,999	0.1495	0.3084	0.485	0.628	0.0324	0.2448	0.132	0.895
$100,000-$199,999	1.1840	0.2880	4.111	<0.001	0.9617	0.2296	4.189	<0.001
$200,000 or more	1.9617	0.3002	6.536	<0.001	1.6214	0.2422	6.695	<0.001
Housing type: Multi-family	-0.0432	0.2680	-0.161	0.872	-0.2522	0.2386	-1.057	0.291
Housing tenure: Rent	-0.6404	0.2337	-2.740	0.006	-0.7136	0.2014	-3.543	<0.001
Accessibility to public EV charging stations	0.0093	0.0015	6.127	<0.001	0.0084	0.0013	6.506	<0.001
	Model 4a: Urban				**Model 6a: Urban**			
Intercept	-5.7344	0.3977	-14.419	<0.001	-4.7732	0.3272	-14.590	<0.001
Number of household vehicles[a]	0.3759	0.0596	6.307	<0.001	0.3120	0.0538	5.795	<0.001
Age of responding adult[b] (categories 1–11)	-0.0872	0.0484	-1.801	0.072	-0.1107	0.0421	-2.633	0.008
Highest education level: College degree	0.6475	0.2058	3.147	0.002	0.6298	0.1749	3.602	<0.001
Household income: $50,000-$99,999	0.1642	0.3405	0.482	0.630	0.0911	0.2764	0.330	0.742
$100,000-$199,999	1.0253	0.3212	3.192	0.001	0.8150	0.2632	3.096	0.002
$200,000 or more	1.7370	0.3351	5.183	<0.001	1.4547	0.2777	5.239	<0.001
Housing type: Multi-family	-0.0975	0.2949	-0.331	0.741	-0.3438	0.2677	-1.285	0.199
Housing tenure: Rent	-0.6154	0.2511	-2.451	0.014	-0.6775	0.2208	-3.068	0.002
Accessibility to public EV charging stations	0.0124	0.0020	6.177	<0.001	0.0100	0.0017	5.737	<0.001
	Model 4b: Rural				**Model 6b: Rural**			
Intercept	-5.2591	0.8331	-6.313	<0.001	-5.3508	0.7263	-7.367	<0.001
Number of household vehicles[a]	-0.3378*	0.1529	-2.209	0.027	0.0009*	0.1148	0.008	0.994
Age of responding adult[b] (categories 1–11)	-0.0459	0.0915	-0.502	0.616	0.0161	0.0813	0.198	0.843
Highest education level: College degree	0.8928	0.4845	1.843	0.065	1.1981	0.4361	2.747	0.006
Household income: $50,000-$99,999	0.1393	0.8397	0.166	0.868	-0.4030	0.7107	-0.567	0.571
$100,000-$199,999	1.8974	0.7454	2.546	0.011	1.4571	0.6052	2.407	0.016
$200,000 or more	3.1610~	0.7757	4.075	<0.001	2.3362	0.6402	3.649	<0.001
Housing type: Multi-family	0.3005	0.7500	0.401	0.689	0.3534	0.7126	0.496	0.620
Housing tenure: Rent	-1.4792	0.8547	-1.731	0.084	-1.6039	0.8215	-1.952	0.051
Accessibility to public EV charging stations	0.0115	0.0162	0.708	0.479	0.0116	0.0143	0.811	0.417

Sample size (N = 8,894).

Goodness-of-fit statistics, BEV: Null model (LL = -1,343), Model 3 (LL = -1,180, McFadden pseudo-R^2 = 0.121), Model 4 (LL = -1,162, McFadden pseudo-R^2 = 0.135).

Goodness-of-fit statistics, BEV/PHEV: Null model (LL = -1,722), Model 5 (LL = -1,522, McFadden pseudo-R^2 = 0.116), Model 6 (LL = -1,508, McFadden pseudo-R^2 = 0.124).

[a] The coefficient is for the number of household vehicles – 1.

[b] The coefficient is for the age category – 4.

* Significant difference (p<0.05) for rural vs. urban. ~ Marginally significant difference (p<0.10) for rural vs. urban.

In Model 3 (statewide, BEV only), the likelihood of BEV ownership increased substantially with household income. Compared to the lowest income category (less than $50,000), households with incomes $100,000–$199,999 had more than 200% greater odds of having a BEV (odds ratio (OR) = $e^{Exp.}$ = 3.267), increasing to more than 600% greater odds for households with incomes $200,000 or more (OR = 7.111). There was no significant difference in EV adoption for households directly on either side of a $50,000 income threshold. Households with more vehicles were also more likely to have a BEV: 28% greater odds for each additional vehicle (OR = 1.282). Education had a meaningful and statistically significant effect (OR = 1.989), suggesting that households with a college degree are about twice as likely to own a BEV. Contrary to expectations, the age of the responding adult was not statistically significantly associated with BEV adoption; although the estimated coefficient showed a negative trend of lower adoption with increasing age. Similarly, residents of multi-family housing were not significantly more or less likely to have a BEV, all else equal. Instead, residential type played a significant role: The odds of having a BEV were about half for renters (OR = 0.527) as compared to homeowners. Accessibility to public EV charging stations was a significant but modest predictor (OR = 1.009, $e^{10 \times Est.}$ = 1.098), with the results indicating that improving charging access by 10 points might increase the odds of BEV ownership by nearly 10%.

When comparing magnitudes of the estimates between urban and rural residents (Model 4), results were largely similar, but with a few important differences. Households more likely to have a BEV in both urban and rural areas had the following characteristics: a higher income, a college degree, and a homeowner. Younger responding adults and greater access to public EV charging increased the odds of having a BEV, and although the effects were not significant for rural households only (Model 4b), the differences were not statistically significant. The highest income category was more positively associated with BEV adoption in rural areas, indicating a potentially stronger income effect there. The biggest difference was the diverging effect of vehicle ownership on EV adoption: Having more vehicles was linked to greater BEV adoption among urban households, but actually lower BEV adoption among rural households. Specifically, each additional vehicle would yield a 46% increase in the odds of having a BEV in urban areas but a 29% decrease in the odds of having a BEV in rural areas. This result could hint at how EVs fit into household's mobility tools: They may be considered an "extra" vehicle in urban areas but are the "primary" vehicle for rural households.

Model 5 (statewide, BEV/PHEV) showed results that were largely consistent with Model 3, though some associations shifted slightly in magnitude. Income remained a strong and significant predictor of EV adoption, although the magnitudes were smaller ($OR_{\$100,000\text{-}\$199,999}$ =

2.616, $OR_{\$200,000 \text{ or more}}$ = 5.060). Vehicle ownership, holding a college degree, being a homeowner, and having greater access to public EV charging were all still positively associated with EV adoption, with roughly similar magnitudes of effect. The one difference is that age was now significant, with older adults being less likely to have an EV (OR = 0.925). For Model 6 (urban vs. rural, BEV/PHEV), any differences largely mirrored those discussed for Model 4 (urban vs. rural, BEV). This time, while vehicle ownership was positively associated with EV adoption among urban households (OR = 1.366), there was no association between vehicle ownership and EV adoption among rural households in Model 6, rather than a negative association with BEV adoption in Model 4.

3.5.3 Summary of Key Findings

These patterns provide important insight into the varying influences on EV ownership across Utah's urban and rural areas. Empirically, the factors influencing EV adoption (Table 3.3) remain largely the same across urban/rural contexts: EVs are more likely among households having higher income, with a college-educated adult, owning a home (rather than renting), and with greater access to public EV charging stations. This suggests that similar factors may be motivating EV ownership in urban and rural areas of Utah, at least among early adopters (as of 2023), and that urban form and regional differences may be less important at this relatively early stage of technological adoption.

The one EV adoption factor that was consistently different was vehicle ownership. In the urban models and the statewide models (within which the urban population dominates), households with more vehicles were significantly more likely to own at least one EV (a BEV or PHEV). Based on the vehicle ownership models (Table 3.2), these households were more likely to have higher incomes and be larger (more adults, especially workers, and more children). These results may indicate that EVs are often acquired as secondary or additional vehicles in multi-car urban households, allowing households to test EV suitability while maintaining conventionally fueled vehicles for longer trips or rural/recreational travel. On the other hand, in rural areas, the relationship between vehicle ownership and EV adoption was nonexistent (Model 6b) or even negative (Model 4b). This result suggests that EV adoption among rural households may not be additive but instead a substitution or trade-off decision (i.e., replacing a gas-powered vehicle) constrained by practicality or vehicle versatility. Overall, these findings highlight the importance of understanding household vehicle fleet composition and motivations when assessing EV adoption behavior.

Across all models, household income emerged a strong and consistent predictor of EV adoption, even more so than for vehicle ownership. Especially households with incomes of $200,000 or more, and even those with incomes $100,000–$199,999, were much more likely to have EVs than households with less than $100,000 income. This key finding aligns with existing results (Kumar & Alok, 2020; Sadeghvaziri et al., 2024) that EVs, particularly newer models, still tend to be more expensive up front than traditional vehicles. However, as more EVs come to market and the used EV market expands with greater supply, the cost of obtaining an EV may come down and the role of income in EV adoption may diminish, somewhat.

Education also showed a strong and consistent association with EV adoption, in both urban and rural areas. Households with a college degree were around twice as likely to adopt an EV than households without a college degree. This may suggest greater awareness, access to information, or pro-environmental values that are more prevalent among highly educated individuals. Interestingly, this finding is contrary to some research (Bindhya et al., 2025; Rahman et al., 2025) showing little influence of education. This suggests that education may influence adoption not only through economic means but also potentially through values and access to information.

Age, on the other hand, showed only a modest (and sometimes non-significant) relationship with EV adoption. As the age of the responding adult increased, EV adoption decreased slightly. The fact that age was not a stronger factor could be due to not representing non-linear effects. Another explanation is due to the imprecise measure, in which only the age of the responding adult was used as a proxy for unmeasured social or psychological factors. We suggest that future surveys try to measure (and subsequently model the influence of) various subjective and perceptual factors that may affect EV adoption, beyond age and educational attainment.

The type of housing (single-family versus multi-family housing) was not a significant factor affecting EV adoption. Instead, housing tenure was strong and (usually) statistically significant across all modes: Overall, renters were around half as likely to have an EV than homeowners. These results could reflect an overall lack of ability of renters to install home charging; renters may also be less likely to have access to private garages or driveways that enable home charging. To promote ubiquitous EV adoption, it is critical to address structural barriers like these. Strategies may include expanding curbside or community charging stations, offering incentives to rental residential property owners for charger installation, and updating new building/parking requirements to provide for a minimum number of EV charging spaces.

As an alternative to home charging, accessibility to public EV charging infrastructure seems to play a positive (albeit fairly modest) role in household EV adoption, across most models. This may reflect the early stage of EV infrastructure deployment in Utah, or the fact that many early adopters rely primarily on home charging. Nonetheless, its consistent presence as a positive factor, especially in urban areas, highlights the importance of continued investment in public charging, particularly for those who may lack access to private charging at home or work.

Finally, the rural vs. urban differences revealed by the interaction models underscore how contextual and infrastructural factors shape EV adoption. The greater influence of high incomes in facilitating EV adoption among rural households highlights economic disparities that may make owning an EV more challenging in rural areas. Also, the no effect or negative effect of vehicle ownership on EV adoption among rural households (compared to a positive effect among urban households) could suggest different motives for EV adoption: as a second (or third) vehicle in urban areas but as a primary vehicle in rural areas. Corroboration of this conclusion would require an analysis of how EVs are being used by urban versus rural households, which is the focus of a different analysis.

3.6 Conclusions

This study provides a comprehensive analysis of EV adoption across Utah, with a particular focus on the socio-economic, infrastructural, and geographic factors influencing household decisions to own BEVs and PHEVs. Against the backdrop of Utah's rapid growth, pressing air quality concerns, and the upcoming 2034 Winter Olympics, understanding these dynamics is critical to developing targeted policies that support a sustainable transportation future.

Our findings reinforce what much of the literature has suggested: Income remains the most consistent and influential predictor of both vehicle ownership and EV adoption across all models. Households with higher financial capacity are more likely to own multiple vehicles and adopt EVs, underscoring the need for financial incentives and affordability strategies to expand adoption among lower-income populations. Other variables, including higher education, homeownership, and access to public charging infrastructure, are influential and supportive of EV uptake. The explanation for these findings is likely due to a combination of perceptions or attitudes toward EVs, easier access to EV charging at home or on-the-go, and greater financial resources given higher EV purchase prices. While most EV adoption factors were similar in urban and rural areas, the few significant differences (for high income and vehicle ownership) point to the need for continued monitoring of EV adoption trends. This also highlights the potential for regionally targeted strategies such as EV charging infrastructure investment in rural areas, financial incentives tailored to lower-income groups, and behavioral interventions that build awareness and familiarity with EV technology. Overall, this study contributes to a more localized and nuanced understanding of EV adoption, providing a foundation for meeting the diverse transportation needs and constraints of Utah's communities.

3.7 Acknowledgments

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4.0 EV TRAVEL BEHAVIORS IN URBAN AND RURAL UTAH

4.1 Abstract

This study examines daily travel behavior of electric vehicles (EVs) and EV-owning households in Utah, with particular attention to differences across urban and rural contexts. Using data from the 2023 Utah Moves Household Travel Survey, we analyzed household- and vehicle-day travel outcomes, including trip frequency, distance, and duration. Statistical models were estimated to assess the influence of socio-demographic, household, and geographic factors, with interaction terms testing how EV ownership effects differ in urban versus rural settings. Separate models examined just BEVs versus either BEVs or PHEVs; findings were largely similar. Results indicate that household structure (workers, students, children) and income strongly shape travel participation and intensity, while older age groups are consistently associated with reduced household travel. Vehicle availability is a robust predictor of trip frequency, distance, and duration. Although EV-owning households did not exhibit statistically significant differences in travel outcomes compared to non-EV households, EVs themselves are less likely to not be used on a given day, and they make more daily trips, at least in urban areas. Additionally, regional contrasts are evident: Rural households show stronger income effects, with higher-income rural households traveling substantially more than their lower-income counterparts, whereas urban households exhibit smaller income-related differences in travel. Overall, the findings suggest that EV ownership itself does not substantially alter daily travel patterns once household and demographic characteristics are considered, but spatial context amplifies socioeconomic differences in mobility. These insights provide an empirical foundation for understanding EV travel behavior and use across diverse geographic settings, offering guidance for planners and policymakers seeking to support sustainable transportation transitions.

4.2 Introduction

The use of electric vehicles (EVs) for transportation presents significant opportunities to reduce greenhouse gas emissions and reliance on fossil fuels (Wu & Zhang, 2017). However, their integration into everyday travel behavior is shaped by a complex interaction of social, economic, and geographic factors. Among these, differences between urban and rural communities are particularly critical, as infrastructure availability, travel needs, and EV adoption patterns vary substantially across spatial contexts (Wood et al., 2017). Knowledge about how EVs are used (or not) in different contexts can aid in establishing more accurate predictions of travel demand and energy use, which would aid transportation planners and electricity grid managers.

A limited but growing body of research has shown that EV travel behavior can differ in meaningful ways from travel utilizing internal combustion engine (ICE) vehicles. Longer-range battery EVs tend to be used more frequently and displace more ICE travel, while short-range EVs are often supplemented with gasoline vehicles for longer trips, limiting their overall impact (Tal et al., 2020). Range constraints also shape trip decisions: Discretionary trips may be canceled or shifted to closer destinations, while work trips are more likely to shift modes than be canceled (Langbroek et al., 2018). Daily travel distances for EV users are generally shorter than for ICE users, largely due to range and charging limitations (Wu et al., 2018). Beyond vehicle characteristics, socio-economic differences such as income influence how households adapt to range constraints and charging access. Built environment factors further contribute to differences: EV registrations are disproportionately concentrated in urban areas, where shorter trips, higher density, and supportive policies encourage adoption, while rural areas face challenges such as longer trip distances, sparse charging infrastructure, and fewer vehicle options (Wood et al., 2017). Trip purposes also matter, with home-based work trips dominating most EV use, while company-owned EVs used for non-home-based purposes travel significantly farther (Wang et al., 2024). Together, existing research highlights that EV travel patterns are shaped by the interaction of vehicle technology, socio-demographic factors, and spatial context, underscoring the need to distinguish between urban and rural EV use.

Building on these insights, Utah provides a good case study for exploring these dynamics. The state continues to face challenges related to air pollution, and a transition toward cleaner transportation options such as EVs could play an important role in improving air quality. Yet, little is known about how travel behavior differs between EV and non-EV users, including in Utah's urban and rural areas. Understanding these patterns is essential for identifying barriers to EV adoption and use, and for informing policies that leverage EVs as effective tools for sustainable mobility. By analyzing household travel survey data and vehicle use patterns, this study aims to address three key research questions:

1. How does daily trip frequency and travel distance and duration differ between EV and non-EV households, and between EVs and ICE vehicles?
2. How do these patterns vary across Utah's urban and rural settings?
3. What socio-demographic factors are associated with EV use in these contexts?

This paper offers one of the first systematic analyses of EV travel behavior in Utah, providing insights into how regional differences shape EV use and informing strategies to support more effective EV adoption across various types of communities.

4.3 Literature Review

In this research, we are measuring travel behavior in the aggregate, as the act of traveling, the number of trips, total distance traveled, and cumulative trip durations, both by household and per vehicle. There is considerable scientific literature on travel behaviors and their influences. This literature shows that travel behavior is shaped by factors such as socio-demographics (like age and gender), household resources (income and mobility tools like automobiles), and the built environment.

Age, gender, and car ownership strongly affect travel patterns. For instance, Abdollahzadeh Kalantari et al. (2025) show the influence of these factors on e-scooter choice: Younger adults adopt them more readily; older adults cite safety and tech barriers; men ride slightly more than women (though women show high latent demand); and many users come from car-owning households but choose scooters for convenience, parking, or fuel cost reasons. While Martin et al. (2016) highlight broader socio-demographic effects, they show that gender roles, household structure, income, and urban/rural location significantly shape trip frequency, mode choice, and trip chaining. Also, women and single parents make more complex trip chains; income affects trip length and transit use; and urban households show higher transit usage at all income levels (Martin et al., 2016).

Empirical research confirms that trip frequency, distance, and duration vary systematically across income and age groups and are sensitive to both built environment and policy conditions. Choi et al. (2014) find that higher-income and younger households make more trips, travel longer distances, and show pronounced peak-period travel, while lower-income households display flatter temporal patterns and shorter average trip distances. Lee et al. (2023) show that external shocks such as COVID-19 lead to substantial reductions in trip frequency, especially for discretionary trips and transit use, while essential commuting trips remain more regular. They also report that car users shifted toward shorter trips, preserving daily activity space but reducing overall trip counts. Longitudinal evidence from Schlich and Axhausen (2003) indicate that travel behavior has both stable and variable components; commuting trips and core destinations are highly repetitive, whereas discretionary trips introduce day-to-day variability, particularly on weekends.

Extending the current understanding of travel behavior regardless of the fuel type of vehicles in a household, it is important to focus on how EVs might introduce distinct patterns shaped by socio-demographic and built environment factors. While many determinants of travel behavior apply to all vehicle users, EV-specific constraints such as range, charging availability, and energy efficiency create unique adaptations in trip-making and daily activity patterns. These constraints and opportunities highlight differences not only in how people adopt EVs but also in how they use them across urban and rural settings. Despite limited empirical studies, some findings are emerging regarding EV use and explanatory factors.

Socio-demographic conditions strongly affect EV travel behavior. Tal et al. (2020) found that households with longer-range BEVs drove more of their total miles on electricity, displaced more conventional vehicle miles, and realized greater GHG reductions than PHEV households. However, Langbroek et al. (2018) observed that lower-income respondents were more likely to add discretionary trips when sufficient EV range was available, reflecting a rebound effect that could offset environmental benefits. Wu et al. (2018) further demonstrated that EV users' acceptable daily travel distances are shorter than those of ICE users, shaped by range and charging constraints. Together, these studies suggest that while EVs contribute to emissions reductions, socio-demographic factors such as income levels and adaptation strategies significantly influence the extent of their environmental and behavioral impacts.

The built environment also plays a critical role in shaping EV travel patterns. Wood et al. (2017) noted that 91% of existing PEV registrations are concentrated in urban areas, where shorter trip distances, higher density, and supportive policies encourage adoption. In contrast, rural areas face longer average trip lengths, sparse infrastructure, and slower adoption. Range limitations further shape behavior: Langbroek et al. (2018) showed that under restricted range, drivers often canceled discretionary trips, switched to closer destinations, or rescheduled, while work trips were rarely canceled. With abundant range, EV users tended to increase shopping and leisure travel, sometimes shifting from public transit to EVs. Wang et al. (2024) also highlighted variations by trip type, with home-based work trips dominating daily EV use, while company-owned EVs engaged in non-home-based trips covered significantly longer distances. These findings illustrate that EV travel patterns are deeply embedded in the built environment, with urban and rural contexts producing distinct opportunities and challenges for adoption and use.

4.4 Methodology

4.4.1 Data Sources

The main data source of this study was the 2023 Utah Moves Household Travel Survey, provided by the Wasatch Front Regional Council (WFRC). The Utah Moves Survey employed a multi-modal approach (smartphone app, web, and phone) to capture both household demographics and individual travel behavior across Utah (RSG, 2024). It included a recruitment survey, a travel diary, and supplemental surveys, and ultimately collected responses from more than 11,000 households between February and June 2023. Our analysis focused on the Household Travel Survey (HTS) component, which included information on household and personal characteristics, as well as indicators of whether households owned battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), or non-electric ICE vehicles. Transportation information was collected for each household member via a travel diary for either one day (for web and phone users) or for up to seven consecutive days (for smartphone app users). After initial cleaning, our working sample included data from 11,183 unique households.

Because travel decisions are often coordinated at the household level and vehicles may be shared among household members, we structured our analysis at the household level. We processed the HTS data (household, person, vehicle, day, and trip tables) into two daily datasets:

- **Household travel behaviors**: Daily travel outcomes were aggregated for each household across all person–trips reported in a survey day. We calculated the total number of trips, total distance traveled, and total travel time. For instance, if one adult drives two miles (ten minutes) to school, picks up a child, and drives the same distance/duration home, this would be counted as three trips, six miles, and thirty minutes. We also noted if no household members traveled on the day.
- **Vehicle travel behaviors**: Daily travel outcomes were also aggregated for each household vehicle on each day. We computed the same three travel behavior outcomes (trip frequency, distance, and duration) for vehicles' daily travel.[2] In the same example presented for household travel behavior, this would be counted as two trips, four miles, and twenty minutes. We also noted if the vehicle was not used on the day.

When processing both datasets, we removed household days and vehicle days when the household did not have complete travel records on the particular day (i.e., some trips were missing). This allowed us to aggregate and compare daily travel outcomes consistently across households regardless of the number of reporting days. We also removed records with missing data on key independent variables, and no household weights (due to the need to weight the data for non-representativeness). This reduced the sample to 7,752 unique households.

The descriptive statistics of the dependent variables are summarized in Table 4.1 for household travel behaviors and Table 4.2 for vehicle travel behaviors. At the household–day level (N = 16,085), 11% of households reported no travel on a survey day, while traveling households averaged 8.5 person–trips, 118 miles, and 161 minutes per day. The median traveling household took 6 person–trips and traveled 28 miles in 92 minutes. Comparing regions, urban households were slightly more likely than rural households to not travel (11.6% vs. 10.1%),

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[2] Joint trips by members of a household were not always recorded consistently. For instance, two adults might fill out separate online diaries with different activity times. Or smartphone apps on two different phones might identify the start or end of a trip slightly differently. Therefore, we wrote a custom script (Paskett & Singleton, 2026) to identify likely joint trips using the same vehicle, considering same vehicle mode, multiple travelers, common origins and destinations, and similar arrival and departure times (± 5 minutes).

whereas rural traveling households made slightly more person–trips and traveled slightly longer distances and durations (on average) than urban traveling households (8.7 vs. 8.4 trips, 126 vs. 115 miles, 166 vs. 158 minutes). At the vehicle–day level (N = 25,003), nearly half (44%) of household vehicles recorded no trips on a given day. Active vehicles averaged 4.6 trips, 50 miles, and 86 minutes per day; median daily values were lower at 4 vehicle–trips and 19 miles and 55 minutes driven. Comparing regions, rural vehicles were more likely to be not driven than urban vehicles (47.5% vs. 42.6%), but active vehicles were used for roughly the same number of vehicle–trips, distances, and durations in urban areas as compared to rural areas (4.6 vs. 4.7 trips, 51 vs. 48 miles, 86 vs. 88 minutes).

Table 4.1: Descriptive statistics of dependent variables for household travel behaviors

	Categorical			*Continuous*		
Variable	*N*	*#*	*%*	*Mean*	*SD*	*10th, 50th, 90th Percentiles*
Dependent variables						
Household did not travel	16,085					
True		1,794	11.15			
False		14,291	88.85			
Travel outcomes (all modes)	14,291					
Number of person–trips (#)				8.50	7.42	2, 6, 17
Distance traveled (miles)				118.18	1,010.62	4, 28, 160
Travel time (minutes)				160.57	227.56	24, 92, 349

Table 4.2: Descriptive statistics of dependent variables for vehicle travel behaviors

	Categorical			*Continuous*		
Variable	*N*	*#*	*%*	*Mean*	*SD*	*10th, 50th, 90th Percentiles*
Dependent variables						
Vehicle was not used	25,003					
True		11,040	44.15			
False		13,963	55.85			
Travel outcomes (all modes)	13,963					
Number of vehicle–trips (#)				4.63	3.11	2, 4, 9
Distance traveled (miles)				50.32	363.61	4, 19, 83
Travel time (minutes)				86.48	128.17	16, 55, 161

Independent variables are summarized in Table 4.3 for household–day data (N = 16,085) and Table 4.4 for vehicle–day data (N = 25,003). In both datasets, the independent variables included household structure (e.g., number of workers, non-workers, excess jobs, children, and students), socio-demographics (e.g., age of responding adult, number of vehicles, household income categories), and housing and built environment factors (e.g., housing type, housing tenure, region). For simplicity, and due to sample size limitations, we categorized households as "urban" if they lived within the Wasatch Front region—specifically, the WFRC and Mountainland Association of Governments (MAG) metropolitan planning organization (MPO) boundaries covering the Salt Lake City, Provo–Orem, and Ogden–Layton metropolitan areas—and "rural" if they lived anywhere else in Utah. For household travel behaviors, we included a binary indicator for whether the household owned an EV (BEV or BEV/PHEV). For vehicle travel behaviors, we included a binary indicator for whether the vehicle was an EV (BEV or BEV/PHEV).

Table 4.3: Descriptive statistics of independent variables for household–day

	Categorical		*Continuous*		
Variable	*#*	*%*	*Mean*	*SD*	*10th, 50th, 90th Percentiles*
Independent variables					
Number of household vehicles			1.55	1.04	1, 1, 3
Number of non-workers			0.63	0.80	0, 0, 2
Number of workers			1.18	1.01	0, 1, 2
Number of excess jobs[a]			0.17	0.49	0, 0, 1
Number of children (age < 18)			0.22	0.75	0, 0, 1
Number of students			0.40	0.89	0, 0, 1
Age of responding adult (categories 1–11[b])			6.62	1.88	4, 6, 9
Household income: Under $50,000	6,557	40.76			
$50,000-$99,999	5,576	34.67			
$100,000-$199,999	3,283	20.41			
$200,000 or more	669	4.16			
Housing type: Single-family	9,800	60.93			
Multi-family	6,285	39.07			
Housing tenure: Own	8,845	54.99			
Rent	7,240	45.01			
Region: Urban (Wasatch Front)	11,621	72.25			
Rural (outside Wasatch Front)	4,464	27.75			
Household has a BEV: True	321	2.00			
False	15,764	98.00			
Household has a BEV/PHEV: True	429	2.67			
False	15,656	97.33			

[a] Excess jobs is defined as the total number of household jobs minus the total number of workers.
[b] Age categories: 1: under 5, 2: 5–15, 3: 16–17, 4: 18–24, 5: 25–34, 6: 35–44, 7: 45–54, 8: 55–64, 9: 65–74, 10: 75–84, 11: 85 or older.

Together, these variables capture key household, demographic, and geographic characteristics that are used to explain variation in the dependent variables (travel outcomes). They provide the contextual and behavioral background necessary to model daily travel behaviors at both household and vehicle levels. At the household–day level (Table 4.3), on average, households owned 1.6 vehicles, had 1.2 workers and 0.6 non-workers, and had 0.2

children and 0.4 students. The average respondent age corresponded to the 35–44 group (mean category = 6.6). About 41% of households earned less than $50,000 annually, while almost 25% earned $100,000 or more. Most lived in single-family homes (61%) and owned their housing (55%). About 2% of households reported owning a BEV, and 2.7% reported owning a BEV or PHEV. Results were somewhat similar in the vehicle–day dataset (Table 4.4), which excludes households with zero vehicle ownership. These households owned more vehicles (2.3), although BEVs were only 1.4% and BEV/PHEVs were only 1.9% of observations. Fewer households were lower-income (30%) and more were higher-income (34%), and they were more likely to live in single-family homes (74%) and own their housing (66%).

Table 4.4: Descriptive statistics of independent variables for vehicle–day data

	Categorical		*Continuous*		
Variable	*#*	*%*	*Mean*	*SD*	*10th, 50th, 90th Percentiles*
Independent variables					
Number of household vehicles			2.25	1.28	1, 2, 4
Number of non-workers			0.70	0.85	0, 0, 2
Number of workers			1.35	1.11	0, 1, 3
Number of excess jobs[a]			0.19	0.52	0, 0, 1
Number of children (age < 18)			0.30	0.87	0, 0, 1
Number of students			0.39	0.88	0, 0, 1
Age of responding adult (categories 1–11[b])			6.77	1.86	4, 7, 9
Household income: Under $50,000	7,380	29.52			
$50,000-$99,999	9,130	36.52			
$100,000-$199,999	6,904	27.61			
$200,000 or more	1,589	6.36			
Housing type: Single-family	18,440	73.75			
Multi-family	6,563	26.25			
Housing tenure: Own	16,506	66.02			
Rent	8,497	33.98			
Region: Urban (Wasatch Front)	17,208	68.82			
Rural (outside Wasatch Front)	7,795	31.18			
Vehicle is a BEV: True	360	1.44			
False	24,643	98.56			
Vehicle is a BEV/PHEV: True	483	1.93			
False	24,520	98.07			

[a] Excess jobs is defined as the total number of household jobs minus the total number of workers.
[b] Age categories: 1: under 5, 2: 5–15, 3: 16–17, 4: 18–24, 5: 25–34, 6: 35–44, 7: 45–54, 8: 55–64, 9: 65–74, 10: 75–84, 11: 85 or older.

4.4.2 Data Analysis

We applied different statistical models depending on the type and distribution of the dependent variables. First, for binary outcomes (household did not travel, vehicle was not used), we estimated logistic regression models. Second, for count outcomes (trip frequency), we used negative binomial regression models, which are appropriate for count data. Before settling on this specification, we tested log-linear and Poisson regression models, but negative binomial models were superior in model fit and prediction accuracy. Third, for the other continuous travel behavior outcomes (travel distance and duration), we used linear regression models with a natural log-transformed dependent variable. This transformation reduces skewness, stabilizes variance, and allows for multiplicative interpretations of the estimated coefficients. Independent variables in all of the models included the demographic, socioeconomic, housing, and vehicle-related characteristics mentioned earlier (see Table 4.3 and Table 4.4).

The models were estimated using weighted regression, accounting for sampling bias and non-representativeness. The household weights, originally created by the survey vendor, considered geographic sampling probabilities and characteristics such as household size, income, workers, vehicles, and children. We scaled the expansion weights into adjustment weights for better estimation properties. In the household–day data, most weights ranged from 0.03 to 3.99 (90% interval), with a maximum of 36.2. In the vehicle–day data, most weights (90%) ranged from 0.02 to 4.21, with a max weight of 29.5.

All models were initially estimated in a baseline format, statewide, to observe overall trends and relationships. Subsequently, we introduced interaction terms between the built environment context (urban/rural) and all independent variables, to test whether the effects of demographic, socioeconomic, and household factors on travel outcomes differed between these spatial contexts. Also, EV ownership or EVs was specified in two ways: BEV-only, or either BEV or PHEV. See Figure 4.1 for a summary of the variables and models for ease of reference.

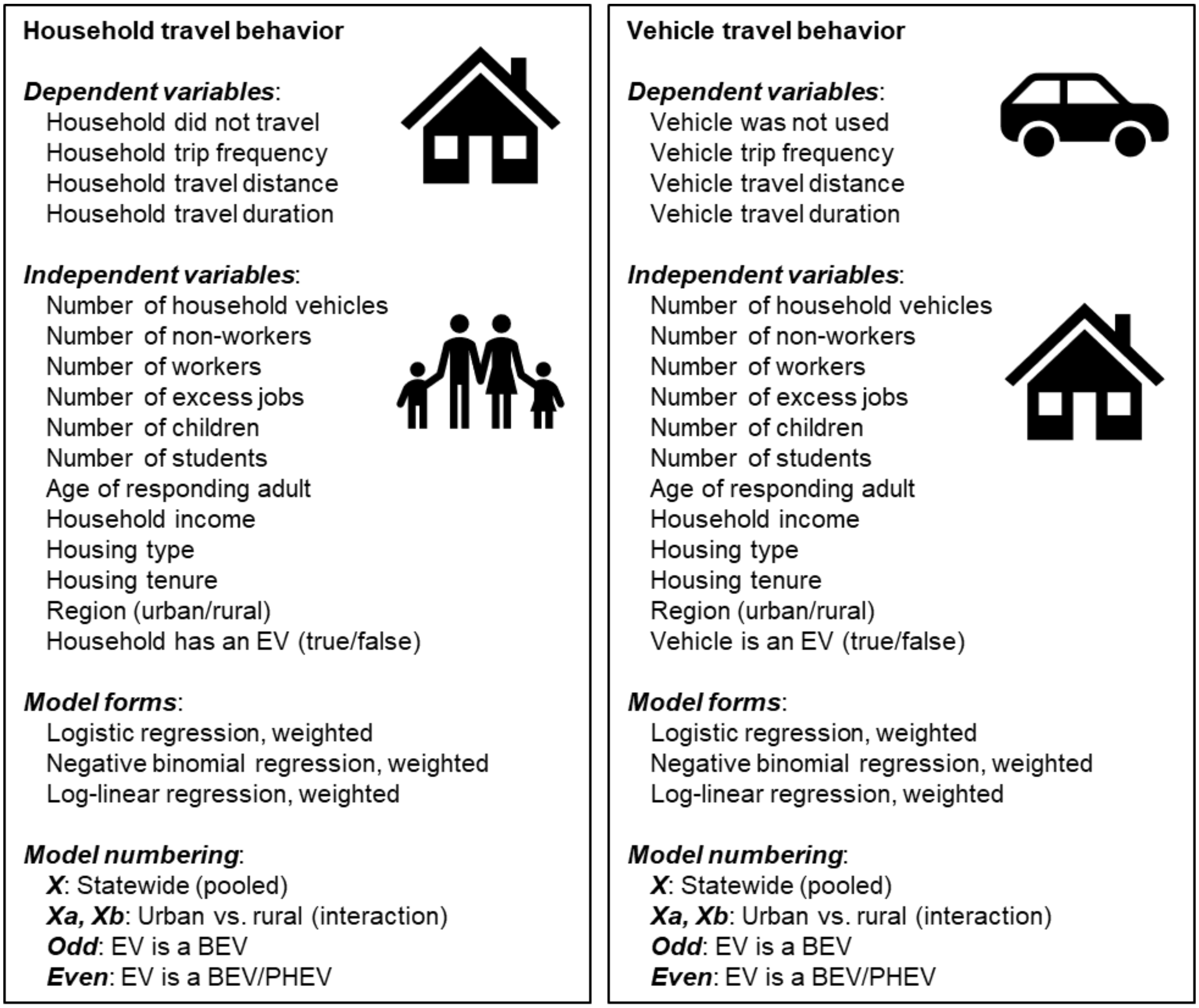

Figure 4.1: Structure of daily household and vehicle travel behavior models

4.5 Results

4.5.1 Household Travel Behavior

4.5.1.1 Household Did Not Travel

Table 4.5 presents the results of logistic regression models estimating the likelihood that a household did not travel on the survey day, separated by EV ownership type (BEV vs. BEV/PHEV) and stratified by urban and rural settings. Across all models, several household demographic and socioeconomic characteristics were significant predictors.

Statewide models (Models 1 and 2) showed that a greater number of household vehicles was strongly associated with a reduced likelihood of not traveling. Household composition also played an important role: Households with more workers, excess jobs, children, and students were significantly less likely to report no travel. Although non-workers appeared to be slightly less likely to not travel, the association was not statistically significant. Income effects were also notable. Relative to the reference group (income <$50,000), higher income categories reduced the odds of not traveling, although there was no statistically significant difference for the highest income category ($200,000 or more). Older respondent age increased the likelihood of not traveling. Rural households were less likely to report no travel compared to urban counterparts. In both the BEV and BEV/PHEV models, EV ownership was not statistically significant; although, the negative coefficients suggest slightly lower odds of not traveling. This suggests that EV ownership itself did not meaningfully change the likelihood of household travel at the statewide level, once demographic and socioeconomic factors are taken into consideration.

Urban models (Models 1a and 2a) largely mirrored the statewide results. Vehicle availability, workers (and non-workers), excess jobs, children, and students all reduced the odds of no travel. Age continued to positively predict not traveling. Among income groups, middle- and higher-income households ($50,000–$199,999) remained less likely to forgo travel. In the urban BEV model (Model 1a), EV ownership remained nonsignificant; however, in the urban BEV/PHEV model (Model 2a) there was marginally significant evidence that EV-owning households might be slightly less likely to not travel; i.e., slightly more likely to travel.

Rural models (Models 1b and 2b) showed some distinct patterns. The effects of more vehicles, workers, excess jobs, children, and students remained significant; although, this was less negative for workers, and non-workers showed a positive (but statistically insignificant) link with not traveling. (The coefficients for non-workers and workers had marginally significant differences for rural versus urban households.) Age appeared to have a stronger positive effect and income appeared to have a stronger negative effect in rural contexts; although the differences were not statistically significant. Like in urban areas, EV ownership did not show any significant association with rural households not traveling, suggesting that broader structural and socioeconomic factors dominate choices to travel (or not) in these settings.

Table 4.5: Results of logistic regression models for household did not travel

Variable	*Household has a BEV* Est.	S.E.	z	p	*Household has a BEV/PHEV* Est.	S.E.	z	p
	Model 1: Statewide				**Model 3: Statewide**			
Intercept	-1.435	0.119	-12.08	<0.001	-1.432	0.119	-12.05	<0.001
Number of household vehicles[a]	-0.214	0.038	-5.69	<0.001	-0.213	0.038	-5.67	<0.001
Number of non-workers	-0.067	0.051	-1.30	0.193	-0.067	0.051	-1.31	0.191
Number of workers	-0.510	0.058	-8.80	<0.001	-0.511	0.058	-8.82	<0.001
Number of excess jobs	-0.349	0.086	-4.08	<0.001	-0.350	0.086	-4.09	<0.001
Number of children (age < 18)	-0.276	0.062	-4.46	<0.001	-0.276	0.062	-4.46	<0.001
Number of students	-0.345	0.064	-5.39	<0.001	-0.344	0.064	-5.37	<0.001
Age of responding adult[b] (categories 1–11)	0.084	0.020	4.19	<0.001	0.084	0.020	4.18	<0.001
Household income: $50,000-$99,999	-0.187	0.064	-2.95	0.003	-0.187	0.064	-2.94	0.003
$100,000-$199,999	-0.218	0.085	-2.57	0.010	-0.212	0.085	-2.50	0.012
$200,000 or more	-0.122	0.160	-0.76	0.448	-0.120	0.160	-0.75	0.452
Housing type: Multi-family	0.033	0.076	0.43	0.668	0.033	0.076	0.43	0.667
Housing tenure: Rent	0.071	0.081	0.87	0.385	0.070	0.081	0.85	0.393
Region: Rural (outside Wasatch Front)	-0.177	0.061	-2.93	0.003	-0.177	0.061	-2.93	0.003
Household has an EV	-0.279	0.244	-1.14	0.252	-0.306	0.206	-1.48	0.139
	Model 1a: Urban				**Model 2a: Urban**			
Intercept	-1.299	0.137	-9.47	<0.001	-1.293	0.137	-9.42	<0.001
Number of household vehicles[a]	-0.251	0.047	-5.37	<0.001	-0.250	0.047	-5.33	<0.001
Number of non-workers	-0.127	0.063	-2.02	0.044	-0.128	0.063	-2.04	0.041
Number of workers	-0.568	0.069	-8.21	<0.001	-0.571	0.069	-8.24	<0.001
Number of excess jobs	-0.294	0.093	-3.17	0.002	-0.294	0.093	-3.17	0.002
Number of children (age < 18)	-0.250	0.070	-3.55	<0.001	-0.249	0.070	-3.54	<0.001
Number of students	-0.370	0.077	-4.80	<0.001	-0.367	0.077	-4.76	<0.001
Age of responding adult[b] (categories 1–11)	0.073	0.023	3.16	0.002	0.073	0.023	3.14	0.002
Household income: $50,000-$99,999	-0.158	0.074	-2.12	0.034	-0.157	0.074	-2.12	0.034
$100,000-$199,999	-0.172	0.097	-1.77	0.076	-0.161	0.097	-1.66	0.097
$200,000 or more	-0.116	0.191	-0.61	0.542	-0.110	0.191	-0.58	0.563
Housing type: Multi-family	0.036	0.088	0.41	0.681	0.036	0.088	0.41	0.682
Housing tenure: Rent	0.007	0.094	0.07	0.941	0.005	0.094	0.06	0.956
Household has an EV	-0.305	0.284	-1.08	0.282	-0.441	0.251	-1.76	0.079
	Model 1b: Rural				**Model 2b: Rural**			
Intercept	-2.080*	0.236	-8.81	<0.001	-2.081*	0.236	-8.81	<0.001
Number of household vehicles[a]	-0.124	0.062	-2.00	0.045	-0.125	0.062	-2.00	0.045
Number of non-workers	0.079~	0.090	0.88	0.380	0.078~	0.090	0.87	0.382
Number of workers	-0.352~	0.109	-3.23	0.001	-0.351~	0.109	-3.23	0.001
Number of excess jobs	-0.570	0.210	-2.72	0.007	-0.569	0.210	-2.71	0.007
Number of children (age < 18)	-0.330	0.131	-2.53	0.011	-0.330	0.131	-2.53	0.011
Number of students	-0.286	0.112	-2.57	0.010	-0.290	0.111	-2.60	0.009
Age of responding adult[b] (categories 1–11)	0.131	0.041	3.21	0.001	0.131	0.041	3.20	0.001
Household income: $50,000-$99,999	-0.263	0.126	-2.08	0.037	-0.264	0.126	-2.09	0.037
$100,000-$199,999	-0.396	0.178	-2.23	0.026	-0.407	0.178	-2.29	0.022
$200,000 or more	-0.113	0.297	-0.38	0.705	-0.129	0.297	-0.44	0.663
Housing type: Multi-family	0.012	0.153	0.08	0.937	0.012	0.153	0.08	0.938
Housing tenure: Rent	0.281	0.162	1.74	0.082	0.284	0.162	1.75	0.080
Household has an EV	-0.244	0.480	-0.51	0.612	-0.008	0.366	-0.02	0.983

Sample size (N = 16,085). Goodness-of-fit statistics, BEV: Null model (LL = -5,625), Model 1 (LL = -5,199, McFadden pseudo-R^2 = 0.076), Model 1ab (LL = -5,190, McFadden pseudo-R^2 = 0.077). Goodness-of-fit statistics, BEV/PHEV: Null model (LL = -5,625), Model 2 (LL = -5,198, McFadden pseudo-R^2 = 0.076), Model 2ab (LL = -5,189, McFadden pseudo-R^2 = 0.077).

[a] The coefficient is for the number of household vehicles – 1. [b] The coefficient is for the age category – 4. Difference for rural vs. urban is: * significant (p<0.05), ~ marginally significant (p<0.10).

4.5.1.2 Household Trip Frequency

Table 4.6 summarizes the negative binomial regression results predicting household trip frequency (number of trips) across statewide, urban, and rural contexts. In the statewide models (Models 3 and 4), a higher number of household vehicles was associated with more trips, reflecting the role of vehicle access in enabling travel. Similarly, more non-workers, workers, excess jobs, and children increased trip frequency. On the other hand, the effect of students was negative and significant, suggesting that households with more students may consolidate trips or rely on alternative travel arrangements. Age of the responding adult had a negative effect, with older households making fewer trips. Income was also a strong predictor: Higher income households consistently recorded more trips, with the strongest effects for incomes above $200,000. Housing type was a significant predictor: Residents of multifamily housing made more trips. Rural residents appeared to make slightly more daily trips than rural residents, but the differences were on the border of marginal statistical significance. EV ownership did not significantly influence trip frequency, whether considering BEV or BEV/PHEV households.

The results of urban models (Models 3a and 4a) were generally consistent with the statewide findings. Vehicle availability, household composition, age, income, and housing type remained strong predictors. Similar to statewide results, EV ownership was not a significant factor in urban areas, indicating that EV households do not travel more or fewer times than non-EV households, once socioeconomic and demographic factors are considered.

The patterns for rural models (Model 3b and 4b) were generally similar but with a few notable differences. Relative to the urban models, the positive associations with excess jobs and with children were weaker for rural households. In contrast, the negative association with students was significant and stronger in rural areas than in urban areas. Respondent age also had a stronger negative effect in rural than in urban contexts, reflecting reduced mobility among older rural households. EV ownership remains nonsignificant, suggesting little behavioral difference between EV and non-EV households in rural areas.

Table 4.6: Results of negative binomial regression models for household trip frequency

Variable	Household has a BEV *Est.*	*S.E.*	*z*	*p*	Household has a BEV/PHEV *Est.*	*S.E.*	*z*	*p*
	Model 3: Statewide				**Model 4: Statewide**			
Intercept	1.661	0.023	72.33	<0.001	1.661	0.023	72.31	<0.001
Number of household vehicles[a]	0.067	0.006	10.53	<0.001	0.067	0.006	10.55	<0.001
Number of non-workers	0.160	0.010	16.74	<0.001	0.159	0.010	16.73	<0.001
Number of workers	0.156	0.009	18.29	<0.001	0.155	0.009	18.27	<0.001
Number of excess jobs	0.082	0.011	7.68	<0.001	0.083	0.011	7.70	<0.001
Number of children (age < 18)	0.299	0.007	44.05	<0.001	0.299	0.007	44.05	<0.001
Number of students	-0.051	0.009	-6.01	<0.001	-0.051	0.009	-6.00	<0.001
Age of responding adult[b] (categories 1–11)	-0.032	0.004	-7.44	<0.001	-0.032	0.004	-7.45	<0.001
Household income: \$50,000-\$99,999	0.078	0.014	5.50	<0.001	0.078	0.014	5.51	<0.001
\$100,000-\$199,999	0.147	0.017	8.49	<0.001	0.148	0.017	8.52	<0.001
\$200,000 or more	0.174	0.029	5.97	<0.001	0.175	0.029	6.03	<0.001
Housing type: Multi-family	0.069	0.016	4.27	<0.001	0.069	0.016	4.27	<0.001
Housing tenure: Rent	-0.012	0.017	-0.67	0.501	-0.012	0.017	-0.67	0.501
Region: Rural (outside Wasatch Front)	0.020	0.012	1.65	0.099	0.020	0.012	1.64	0.102
Household has an EV	0.013	0.037	0.35	0.727	-0.004	0.033	-0.13	0.898
	Model 3a: Urban				**Model 4a: Urban**			
Intercept	1.620	0.027	60.07	<0.001	1.620	0.027	60.05	<0.001
Number of household vehicles[a]	0.059	0.008	7.54	<0.001	0.060	0.008	7.60	<0.001
Number of non-workers	0.164	0.011	14.32	<0.001	0.164	0.011	14.30	<0.001
Number of workers	0.154	0.010	15.30	<0.001	0.154	0.010	15.29	<0.001
Number of excess jobs	0.096	0.012	7.75	<0.001	0.096	0.012	7.77	<0.001
Number of children (age < 18)	0.312	0.008	38.35	<0.001	0.312	0.008	38.35	<0.001
Number of students	-0.022	0.010	-2.17	0.030	-0.022	0.010	-2.17	0.030
Age of responding adult[b] (categories 1–11)	-0.024	0.005	-4.85	<0.001	-0.024	0.005	-4.87	<0.001
Household income: \$50,000-\$99,999	0.089	0.017	5.36	<0.001	0.089	0.017	5.37	<0.001
\$100,000-\$199,999	0.155	0.020	7.70	<0.001	0.156	0.020	7.74	<0.001
\$200,000 or more	0.226	0.034	6.73	<0.001	0.228	0.034	6.79	<0.001
Housing type: Multi-family	0.072	0.019	3.76	<0.001	0.071	0.019	3.75	<0.001
Housing tenure: Rent	-0.014	0.020	-0.68	0.494	-0.014	0.020	-0.68	0.499
Household has an EV	0.024	0.042	0.56	0.573	0.001	0.037	0.02	0.985
	Model 3b: Rural				**Model 4b: Rural**			
Intercept	1.775*	0.042	41.86	<0.001	1.775*	0.042	41.86	<0.001
Number of household vehicles[a]	0.077	0.011	7.03	<0.001	0.077	0.011	7.04	<0.001
Number of non-workers	0.160	0.017	9.18	<0.001	0.160	0.017	9.18	<0.001
Number of workers	0.168	0.016	10.47	<0.001	0.168	0.016	10.45	<0.001
Number of excess jobs	0.037*	0.022	1.72	0.085	0.037*	0.022	1.72	0.085
Number of children (age < 18)	0.264*	0.012	21.34	<0.001	0.264*	0.012	21.33	<0.001
Number of students	-0.115*	0.016	-7.41	<0.001	-0.115*	0.016	-7.41	<0.001
Age of responding adult[b] (categories 1–11)	-0.054*	0.008	-6.47	<0.001	-0.054*	0.008	-6.47	<0.001
Household income: \$50,000-\$99,999	0.068	0.027	2.53	0.011	0.068	0.027	2.53	0.011
\$100,000-\$199,999	0.155	0.035	4.44	<0.001	0.156	0.035	4.45	<0.001
\$200,000 or more	0.022*	0.059	0.38	0.701	0.023*	0.058	0.40	0.688
Housing type: Multi-family	0.064	0.031	2.06	0.040	0.064	0.031	2.05	0.040
Housing tenure: Rent	-0.007	0.033	-0.20	0.841	-0.007	0.033	-0.21	0.837
Household has an EV	0.005	0.081	0.06	0.951	-0.005	0.070	-0.07	0.944

Sample size (N = 14,291). Goodness-of-fit statistics, BEV: Null model (LL = -44,050), Model 3 (LL = -41,813, McFadden pseudo-R^2 = 0.326), Model 3ab (LL = -41,785, McFadden pseudo-R^2 = 0.327). Goodness-of-fit statistics, BEV/PHEV: Null model (LL = -44,050), Model 4 (LL = -41,813, McFadden pseudo-R^2 = 0.326), Model 4ab (LL = -41,785, McFadden pseudo-R^2 = 0.327).

[a] The coefficient is for the number of household vehicles – 1. [b] The coefficient is for the age category – 4. Difference for rural vs. urban is: * significant (p<0.05), ~ marginally significant (p<0.10).

4.5.1.3 Household Travel Distance

Table 4.7 reports the log-linear regression results for household travel distance (in miles) across statewide, urban, and rural contexts. In the statewide models (Models 5 and 6), household vehicle ownership was strongly associated with greater travel distance. More non-workers, workers, excess jobs, and children all significantly increased household travel distance. By contrast, households with more students traveled shorter distances, possibly reflecting localized school travel. Respondent age negatively predicted distance, with older households traveling fewer miles. Income effects were substantial and consistent: Higher income households traveled farther, with the strongest associations among the highest income categories (>$200,000). Housing type and rural region did not significantly affect household distance; although, renters traveled slightly less distance than homeowners. EV ownership was not a significant predictor of travel distance, considering either BEVs or BEV/PHEVs.

Both urban models (Models 5a and 6a) and rural models (Models 5b and 6b) yielded results that largely mirrored those from the statewide models. The only significant difference between the regions was for number of students: The negative impact of students on distances traveled was nearly twice as strong for rural as compared to urban households. EV ownership (BEV or BEV/PHEV) was again not significantly associated with travel distances in both urban and rural areas.

Table 4.7: Results of log-linear regression models for household trip distance

Variable	*Household has a BEV* Est.	*S.E.*	*z*	*p*	*Household has a BEV/PHEV* Est.	*S.E.*	*z*	*p*
	Model 5: Statewide				**Model 6: Statewide**			
Intercept	2.969	0.045	66.53	<0.001	2.970	0.045	66.54	<0.001
Number of household vehicles[a]	0.237	0.013	18.71	<0.001	0.237	0.013	18.75	<0.001
Number of non-workers	0.097	0.019	5.12	<0.001	0.097	0.019	5.10	<0.001
Number of workers	0.158	0.017	9.24	<0.001	0.157	0.017	9.21	<0.001
Number of excess jobs	0.113	0.021	5.25	<0.001	0.113	0.021	5.25	<0.001
Number of children (age < 18)	0.254	0.015	17.48	<0.001	0.254	0.015	17.48	<0.001
Number of students	-0.157	0.017	-9.23	<0.001	-0.156	0.017	-9.20	<0.001
Age of responding adult[b] (categories 1–11)	-0.054	0.008	-6.49	<0.001	-0.054	0.008	-6.50	<0.001
Household income: \$50,000-\$99,999	0.282	0.027	10.37	<0.001	0.282	0.027	10.38	<0.001
\$100,000-\$199,999	0.387	0.034	11.42	<0.001	0.390	0.034	11.48	<0.001
\$200,000 or more	0.524	0.058	9.07	<0.001	0.528	0.058	9.14	<0.001
Housing type: Multi-family	-0.048	0.031	-1.53	0.125	-0.048	0.031	-1.53	0.125
Housing tenure: Rent	-0.060	0.033	-1.81	0.071	-0.061	0.033	-1.83	0.068
Region: Rural (outside Wasatch Front)	-0.006	0.024	-0.26	0.794	-0.007	0.024	-0.28	0.782
Household has an EV	-0.035	0.075	-0.46	0.643	-0.073	0.065	-1.12	0.261
	Model 5a: Urban				**Model 6a: Urban**			
Intercept	2.984	0.052	57.00	<0.001	2.986	0.052	57.01	<0.001
Number of household vehicles[a]	0.240	0.016	15.36	<0.001	0.241	0.016	15.40	<0.001
Number of non-workers	0.097	0.023	4.25	<0.001	0.096	0.023	4.23	<0.001
Number of workers	0.148	0.020	7.34	<0.001	0.148	0.020	7.31	<0.001
Number of excess jobs	0.117	0.025	4.71	<0.001	0.117	0.025	4.72	<0.001
Number of children (age < 18)	0.259	0.017	14.83	<0.001	0.259	0.017	14.83	<0.001
Number of students	-0.123	0.020	-6.03	<0.001	-0.123	0.020	-6.01	<0.001
Age of responding adult[b] (categories 1–11)	-0.060	0.010	-6.14	<0.001	-0.060	0.010	-6.15	<0.001
Household income: \$50,000-\$99,999	0.257	0.032	8.02	<0.001	0.257	0.032	8.02	<0.001
\$100,000-\$199,999	0.383	0.039	9.77	<0.001	0.385	0.039	9.82	<0.001
\$200,000 or more	0.503	0.067	7.49	<0.001	0.505	0.067	7.52	<0.001
Housing type: Multi-family	-0.035	0.037	-0.96	0.339	-0.035	0.037	-0.95	0.341
Housing tenure: Rent	-0.058	0.039	-1.50	0.133	-0.059	0.039	-1.52	0.128
Household has an EV	-0.076	0.085	-0.90	0.367	-0.100	0.074	-1.35	0.178
	Model 5b: Rural				**Model 6b: Rural**			
Intercept	2.935	0.083	35.39	<0.001	2.936	0.083	35.40	<0.001
Number of household vehicles[a]	0.222	0.022	10.15	<0.001	0.222	0.022	10.14	<0.001
Number of non-workers	0.110	0.035	3.17	0.002	0.109	0.035	3.16	0.002
Number of workers	0.194	0.032	5.99	<0.001	0.193	0.032	5.97	<0.001
Number of excess jobs	0.097	0.043	2.25	0.025	0.097	0.043	2.24	0.025
Number of children (age < 18)	0.238	0.027	8.99	<0.001	0.238	0.027	8.99	<0.001
Number of students	-0.218*	0.031	-7.05	<0.001	-0.217*	0.031	-7.02	<0.001
Age of responding adult[b] (categories 1–11)	-0.047	0.016	-2.93	0.003	-0.047	0.016	-2.93	0.003
Household income: \$50,000-\$99,999	0.341	0.052	6.58	<0.001	0.342	0.052	6.59	<0.001
\$100,000-\$199,999	0.395	0.069	5.75	<0.001	0.400	0.069	5.81	<0.001
\$200,000 or more	0.584	0.115	5.08	<0.001	0.594	0.115	5.19	<0.001
Housing type: Multi-family	-0.092	0.060	-1.53	0.125	-0.092	0.060	-1.54	0.125
Housing tenure: Rent	-0.076	0.065	-1.17	0.242	-0.077	0.065	-1.19	0.234
Household has an EV	0.116	0.160	0.72	0.469	0.011	0.137	0.08	0.933

Sample size (N = 14,291). Goodness-of-fit statistics, BEV: Null model (LL = -22,746), Model 5 (LL = -22,562, McFadden pseudo-R^2 = 0.048), Model 5ab (LL = -22,547, McFadden pseudo-R^2 = 0.048). Goodness-of-fit statistics, BEV/PHEV: Null model (LL = -22,743), Model 6 (LL = -22,561, McFadden pseudo-R^2 = 0.048), Model 6ab (LL = -22,547, McFadden pseudo-R^2 = 0.048).

[a] The coefficient is for the number of household vehicles – 1. [b] The coefficient is for the age category – 4. Difference for rural vs. urban is: * significant (p<0.05), ~ marginally significant (p<0.10).

4.5.1.4 Household Travel Duration

Table 4.8 presents the log-linear regression results predicting household travel duration (in minutes) across statewide, urban, and rural contexts. In the statewide models (Models 7 and 8), household vehicle ownership, non-workers, workers, excess jobs, and children were all positively associated with travel duration. In contrast, more students reduced total travel time. Respondent age was also negatively associated with travel duration, indicating that older households travel for shorter time periods. Higher income households consistently reported longer travel times, with the strongest associations found for households earning above \$200,000. Housing type and tenure were not significant predictors, while rural residence shows a marginally significant negative association with trip frequency. EV ownership (BEV or BEV/PHEV) did not significantly influence household daily travel duration at the statewide level.

For urban households (Models 7a and 8a), patterns mirrored statewide findings. For rural households (Models 7b and 8b), most results were similar patterns, although there were three significant differences. The positive association between non-workers and travel times was weaker among rural households. The negative association with age was not significant in rural areas. Also, rural households in the highest income category (> \$200,000) did not travel the most; that was actually for the \$100,000–\$199,999 group. In both urban and rural areas, EV ownership was not linked to any significant differences in total travel time.

Table 4.8: Results of log-linear regression models for household trip duration

	Household has a BEV				*Household has a BEV/PHEV*			
Variable	***Est.***	***S.E.***	***z***	***p***	***Est.***	***S.E.***	***z***	***p***
	Model 7: Statewide				**Model 8: Statewide**			
Intercept	4.014	0.035	114.32	<0.001	4.015	0.035	114.30	<0.001
Number of household vehicles[a]	0.122	0.010	12.21	<0.001	0.122	0.010	12.22	<0.001
Number of non-workers	0.164	0.015	11.01	<0.001	0.164	0.015	11.01	<0.001
Number of workers	0.166	0.013	12.40	<0.001	0.166	0.013	12.39	<0.001
Number of excess jobs	0.129	0.017	7.62	<0.001	0.129	0.017	7.62	<0.001
Number of children (age < 18)	0.286	0.011	25.02	<0.001	0.286	0.011	25.02	<0.001
Number of students	-0.055	0.013	-4.11	<0.001	-0.055	0.013	-4.10	<0.001
Age of responding adult[b] (categories 1–11)	-0.014	0.007	-2.08	0.038	-0.014	0.007	-2.09	0.037
Household income: $50,000-$99,999	0.125	0.021	5.85	<0.001	0.125	0.021	5.86	<0.001
$100,000-$199,999	0.219	0.027	8.22	<0.001	0.220	0.027	8.25	<0.001
$200,000 or more	0.327	0.046	7.19	<0.001	0.328	0.045	7.22	<0.001
Housing type: Multi-family	0.027	0.025	1.12	0.263	0.028	0.025	1.12	0.262
Housing tenure: Rent	0.001	0.026	0.05	0.958	0.001	0.026	0.04	0.968
Region: Rural (outside Wasatch Front)	-0.037	0.019	-1.95	0.052	-0.037	0.019	-1.95	0.051
Household has an EV	-0.035	0.059	-0.60	0.546	-0.044	0.051	-0.86	0.391
	Model 7a: Urban				**Model 8a: Urban**			
Intercept	4.019	0.041	97.59	<0.001	4.020	0.041	97.58	<0.001
Number of household vehicles[a]	0.110	0.012	8.94	<0.001	0.110	0.012	8.96	<0.001
Number of non-workers	0.185	0.018	10.31	<0.001	0.185	0.018	10.30	<0.001
Number of workers	0.175	0.016	11.01	<0.001	0.174	0.016	11.00	<0.001
Number of excess jobs	0.135	0.020	6.91	<0.001	0.135	0.020	6.91	<0.001
Number of children (age < 18)	0.294	0.014	21.45	<0.001	0.294	0.014	21.46	<0.001
Number of students	-0.047	0.016	-2.95	0.003	-0.047	0.016	-2.93	0.003
Age of responding adult[b] (categories 1–11)	-0.022	0.008	-2.93	0.003	-0.022	0.008	-2.94	0.003
Household income: $50,000-$99,999	0.113	0.025	4.48	<0.001	0.113	0.025	4.48	<0.001
$100,000-$199,999	0.204	0.031	6.63	<0.001	0.205	0.031	6.65	<0.001
$200,000 or more	0.386	0.053	7.31	<0.001	0.387	0.053	7.33	<0.001
Housing type: Multi-family	0.013	0.029	0.46	0.647	0.013	0.029	0.46	0.643
Housing tenure: Rent	0.014	0.031	0.45	0.650	0.013	0.031	0.44	0.663
Household has an EV	-0.060	0.067	-0.91	0.364	-0.066	0.058	-1.14	0.254
	Model 7b: Rural				**Model 8b: Rural**			
Intercept	3.967	0.065	60.80	<0.001	3.967	0.065	60.80	<0.001
Number of household vehicles[a]	0.135	0.017	7.85	<0.001	0.135	0.017	7.84	<0.001
Number of non-workers	0.115*	0.027	4.22	<0.001	0.115*	0.027	4.21	<0.001
Number of workers	0.149	0.025	5.85	<0.001	0.148	0.025	5.84	<0.001
Number of excess jobs	0.103	0.034	3.03	0.002	0.103	0.034	3.03	0.002
Number of children (age < 18)	0.271	0.021	13.01	<0.001	0.271	0.021	13.02	<0.001
Number of students	-0.055	0.024	-2.26	0.024	-0.055	0.024	-2.25	0.025
Age of responding adult[b] (categories 1–11)	0.006~	0.013	0.46	0.646	0.006~	0.013	0.46	0.646
Household income: $50,000-$99,999	0.157	0.041	3.86	<0.001	0.158	0.041	3.86	<0.001
$100,000-$199,999	0.265	0.054	4.91	<0.001	0.266	0.054	4.92	<0.001
$200,000 or more	0.147*	0.090	1.63	0.103	0.151*	0.090	1.68	0.094
Housing type: Multi-family	0.063	0.047	1.33	0.185	0.063	0.047	1.32	0.186
Housing tenure: Rent	-0.028	0.051	-0.55	0.584	-0.028	0.051	-0.55	0.580
Household has an EV	0.069	0.126	0.55	0.580	0.036	0.108	0.33	0.739

Sample size (N = 14,291). Goodness-of-fit statistics, BEV: Null model (LL = -21,182), Model 7 (LL = -20,136, McFadden pseudo-R^2 = 0.049), Model 7ab (LL = -20,118, McFadden pseudo-R^2 = 0.050). Goodness-of-fit statistics, BEV/PHEV: Null model (LL = -21,182), Model 8 (LL = -20,136, McFadden pseudo-R^2 = 0.049), Model 8ab (LL = -20,118, McFadden pseudo-R^2 = 0.050).

[a] The coefficient is for the number of household vehicles – 1. [b] The coefficient is for the age category – 4. Difference for rural vs. urban is: * significant (p<0.05), ~ marginally significant (p<0.10).

4.5.2 Vehicle Travel Behavior

4.5.2.1 Vehicle Was Not Used

Table 4.9 shows logistic regression results predicting whether a household vehicle was not used on the survey day, estimated separately for vehicles across statewide, urban, and rural contexts. Many household demographic and socioeconomic characteristics were significant factors across all models.

In the statewide models (Models 9 and 10), the number of household vehicles was a strong predictor, with more vehicles increasing the odds that at least one vehicle remained unused on a given day. Households with more workers, excess jobs, children, and students were less likely to leave vehicles unused, reflecting greater daily mobility needs. Income was also influential: Middle and higher-income households were significantly less likely to have vehicles that did not travel, with fairly consistent effects across all categories above $50,000. The number of non-workers and the age of the main household respondent were not significant predictors. Housing tenure was significant: Renters were less likely to not use their vehicle. There was no statistically significant rural–urban difference in unused vehicles; although, the negative sign suggests rural households may have been slightly less likely to not drive a vehicle. Importantly, EV status mattered considerably: BEVs were significantly less likely to remain unused than ICE vehicles; the association for BEV/PHEVs was negative but not statistically significant. This suggests that EVs are actively incorporated into daily household travel patterns.

When comparing urban models (Models 9a and 10a) and rural models (Models 9b and 10b), results were generally consistent with statewide findings, but a couple of differences emerged. The positive association between vehicle ownership and a vehicle not being used was stronger in urban areas, suggesting a slightly higher reliance on household vehicles among rural households. In urban areas, EVs of all types were much less likely to remain unused, indicating that EVs may be the sole vehicle in many urban households or the one more regularly used in multi-vehicle households. In contrast, EVs for rural households were neither more nor less likely to be used than ICE vehicles, which was a significant difference between the regions.

Table 4.9: Results of logistic regression models for vehicle was not used

Variable	*Vehicle is a BEV*				*Vehicle is a BEV/PHEV*			
	Est.	***S.E.***	***z***	***p***	***Est.***	***S.E.***	***z***	***p***
	Model 9: Statewide				**Model 10: Statewide**			
Intercept	-0.351	0.058	-6.01	<0.001	-0.351	0.058	-6.00	<0.001
Number of household vehicles[a]	0.587	0.015	38.64	<0.001	0.587	0.015	38.61	<0.001
Number of non-workers	-0.016	0.024	-0.70	0.486	-0.016	0.024	-0.69	0.490
Number of workers	-0.263	0.021	-12.43	<0.001	-0.263	0.021	-12.42	<0.001
Number of excess jobs	-0.150	0.028	-5.32	<0.001	-0.150	0.028	-5.35	<0.001
Number of children (age < 18)	-0.187	0.017	-10.84	<0.001	-0.187	0.017	-10.83	<0.001
Number of students	0.063	0.022	2.81	0.005	0.063	0.022	2.81	0.005
Age of responding adult[b] (categories 1–11)	-0.017	0.011	-1.54	0.123	-0.017	0.011	-1.54	0.125
Household income: \$50,000-\$99,999	-0.122	0.037	-3.34	<0.001	-0.123	0.037	-3.35	<0.001
\$100,000-\$199,999	-0.114	0.042	-2.71	0.007	-0.115	0.042	-2.72	0.006
\$200,000 or more	-0.160	0.065	-2.45	0.014	-0.166	0.065	-2.54	0.011
Housing type: Multi-family	-0.058	0.042	-1.38	0.168	-0.057	0.042	-1.35	0.176
Housing tenure: Rent	-0.096	0.043	-2.23	0.026	-0.097	0.043	-2.26	0.024
Region: Rural (outside Wasatch Front)	-0.024	0.030	-0.80	0.426	-0.023	0.030	-0.77	0.442
Vehicle is an EV	-0.160	0.080	-1.99	0.046	-0.107	0.071	-1.52	0.128
	Model 9a: Urban				**Model 10a: Urban**			
Intercept	-0.385	0.070	-5.52	<0.001	-0.382	0.070	-5.49	<0.001
Number of household vehicles[a]	0.619	0.020	31.56	<0.001	0.618	0.020	31.56	<0.001
Number of non-workers	-0.023	0.029	-0.80	0.422	-0.024	0.029	-0.81	0.419
Number of workers	-0.247	0.026	-9.45	<0.001	-0.247	0.026	-9.46	<0.001
Number of excess jobs	-0.133	0.034	-3.93	<0.001	-0.134	0.034	-3.97	<0.001
Number of children (age < 18)	-0.187	0.021	-8.80	<0.001	-0.187	0.021	-8.79	<0.001
Number of students	0.038	0.027	1.37	0.172	0.038	0.028	1.40	0.162
Age of responding adult[b] (categories 1–11)	-0.021	0.013	-1.59	0.111	-0.021	0.013	-1.60	0.110
Household income: \$50,000-\$99,999	-0.119	0.044	-2.69	0.007	-0.120	0.044	-2.69	0.007
\$100,000-\$199,999	-0.114	0.050	-2.25	0.024	-0.112	0.050	-2.21	0.027
\$200,000 or more	-0.187	0.077	-2.44	0.015	-0.189	0.077	-2.46	0.014
Housing type: Multi-family	-0.018	0.050	-0.36	0.718	-0.017	0.050	-0.33	0.738
Housing tenure: Rent	-0.128	0.051	-2.50	0.012	-0.131	0.051	-2.56	0.011
Vehicle is an EV	-0.262	0.092	-2.84	0.005	-0.235	0.082	-2.86	0.004
	Model 9b: Rural				**Model 10b: Rural**			
Intercept	-0.340	0.106	-3.22	0.001	-0.345	0.106	-3.26	0.001
Number of household vehicles[a]	0.549*	0.025	22.25	<0.001	0.549*	0.025	22.26	<0.001
Number of non-workers	-0.025	0.041	-0.62	0.538	-0.024	0.041	-0.60	0.549
Number of workers	-0.308	0.037	-8.34	<0.001	-0.306	0.037	-8.29	<0.001
Number of excess jobs	-0.157	0.051	-3.08	0.002	-0.156	0.051	-3.07	0.002
Number of children (age < 18)	-0.176	0.030	-5.91	<0.001	-0.176	0.030	-5.90	<0.001
Number of students	0.111	0.039	2.85	0.004	0.110	0.039	2.81	0.005
Age of responding adult[b] (categories 1–11)	-0.002	0.020	-0.09	0.931	-0.001	0.020	-0.07	0.941
Household income: \$50,000-\$99,999	-0.125	0.065	-1.91	0.056	-0.126	0.065	-1.93	0.054
\$100,000-\$199,999	-0.119	0.078	-1.53	0.127	-0.129	0.078	-1.65	0.099
\$200,000 or more	-0.138	0.128	-1.08	0.282	-0.152	0.128	-1.19	0.235
Housing type: Multi-family	-0.110	0.081	-1.35	0.177	-0.110	0.081	-1.36	0.174
Housing tenure: Rent	-0.032	0.081	-0.40	0.688	-0.028	0.081	-0.35	0.725
Vehicle is an EV	0.071~	0.171	0.42	0.677	0.193*	0.143	1.35	0.177

Sample size (N = 25,003). Goodness-of-fit statistics, BEV: Null model (LL = -17,160), Model 9 (LL = -15,834, McFadden pseudo-R^2 = 0.077), Model 9ab (LL = -15,823, McFadden pseudo-R^2 = 0.078). Goodness-of-fit statistics, BEV/PHEV: Null model (LL = -17,160), Model 10 (LL = -15,834, McFadden pseudo-R^2 = 0.077), Model 10ab (LL = -15,823, McFadden pseudo-R^2 = 0.078).

[a] The coefficient is for the number of household vehicles – 1. [b] The coefficient is for the age category – 4. Difference for rural vs. urban is: * significant (p<0.05), ~ marginally significant (p<0.10).

4.5.2.2 Vehicle Trip Frequency

Table 4.10 presents negative binomial regression models predicting the number of trips made by household vehicles, estimated across statewide, urban, and rural contexts. For the statewide models (Models 11 and 12), household vehicle count is negatively associated with the number of trips per vehicle, indicating that as more vehicles are available, each vehicle is used less frequently. Household composition showed few associations: Only excess jobs and children were associated with more trips; workers, non-workers, and students showed no significant associations with trip frequency. Age of the responding adult was also positively associated with vehicle trip frequency. Overall, household income, housing type, housing tenure, and region showed no significant effects. Statewide, the association of EV ownership was statistically significant. The positive coefficients suggest that EVs tended to make slightly more trips per day than non-EVs.

Results from the urban models (Models 11a and 12a) generally aligned with statewide models, which is not surprising given the predominance of urban households. The rural models (Models 11b and 12b) showed several differences. Both respondent age and the number of excess jobs were not significant among vehicles in rural households. Additionally, the positive effect of children was weaker in rural areas. There were even significant income effects in the rural models: Moderately higher-income households (those in the $100,000–$199,999 group) tended to make slightly more trips per vehicle. Most importantly, unlike in urban areas, EV ownership (whether measured as BEV or BEV/PHEV) was not associated with vehicle trip frequency among rural households. This suggests that in urban areas, EVs are associated with slightly higher trips per vehicle. Perhaps they are being used for shorter trip lengths and closer destinations. In rural areas, EVs may be used almost as frequently as ICE vehicles.

Table 4.10: Results of negative binomial regression models for vehicle trip frequency

Variable	*Vehicle is a BEV*				*Vehicle is a BEV/PHEV*			
	Est.	***S.E.***	***z***	***p***	***Est.***	***S.E.***	***z***	***p***
	Model 11: Statewide				**Model 12: Statewide**			
Intercept	1.487	0.022	67.88	<0.001	1.487	0.022	67.85	<0.001
Number of household vehicles[a]	-0.036	0.006	-5.72	<0.001	-0.035	0.006	-5.67	<0.001
Number of non-workers	0.005	0.009	0.50	0.614	0.005	0.009	0.49	0.623
Number of workers	-0.004	0.008	-0.44	0.658	-0.004	0.008	-0.45	0.652
Number of excess jobs	0.034	0.010	3.44	<0.001	0.035	0.010	3.48	<0.001
Number of children (age < 18)	0.063	0.006	10.83	<0.001	0.063	0.006	10.81	<0.001
Number of students	-0.002	0.009	-0.21	0.836	-0.002	0.009	-0.23	0.820
Age of responding adult[b] (categories 1–11)	0.010	0.004	2.35	0.019	0.010	0.004	2.32	0.020
Household income: $50,000-$99,999	0.012	0.014	0.87	0.386	0.012	0.014	0.88	0.377
$100,000-$199,999	0.029	0.017	1.74	0.082	0.029	0.017	1.77	0.076
$200,000 or more	-0.005	0.026	-0.18	0.859	-0.002	0.026	-0.08	0.938
Housing type: Multi-family	0.005	0.016	0.33	0.739	0.005	0.016	0.31	0.757
Housing tenure: Rent	0.009	0.017	0.56	0.576	0.010	0.017	0.60	0.546
Region: Rural (outside Wasatch Front)	0.018	0.012	1.55	0.121	0.018	0.012	1.53	0.126
Vehicle is an EV	0.093	0.032	2.92	0.003	0.064	0.028	2.27	0.023
	Model 11a: Urban				**Model 12a: Urban**			
Intercept	1.473	0.026	56.67	<0.001	1.473	0.026	56.64	<0.001
Number of household vehicles[a]	-0.037	0.008	-4.72	<0.001	-0.037	0.008	-4.66	<0.001
Number of non-workers	0.005	0.011	0.45	0.655	0.005	0.011	0.44	0.662
Number of workers	-0.008	0.010	-0.77	0.442	-0.008	0.010	-0.76	0.445
Number of excess jobs	0.053	0.012	4.52	<0.001	0.053	0.012	4.57	<0.001
Number of children (age < 18)	0.074	0.007	10.42	<0.001	0.074	0.007	10.40	<0.001
Number of students	0.002	0.011	0.18	0.857	0.001	0.011	0.12	0.901
Age of responding adult[b] (categories 1–11)	0.016	0.005	3.21	0.001	0.016	0.005	3.19	0.001
Household income: $50,000-$99,999	0.008	0.017	0.51	0.611	0.009	0.017	0.53	0.599
$100,000-$199,999	0.017	0.019	0.88	0.377	0.017	0.019	0.88	0.381
$200,000 or more	0.000	0.031	0.00	0.998	0.002	0.031	0.05	0.957
Housing type: Multi-family	0.004	0.019	0.20	0.845	0.003	0.019	0.17	0.862
Housing tenure: Rent	0.011	0.020	0.57	0.566	0.013	0.020	0.64	0.523
Vehicle is an EV	0.117	0.035	3.30	<0.001	0.093	0.032	2.94	0.003
	Model 11b: Rural				**Model 12b: Rural**			
Intercept	1.544	0.040	38.73	<0.001	1.546	0.040	38.76	<0.001
Number of household vehicles[a]	-0.033	0.010	-3.22	0.001	-0.033	0.010	-3.21	0.001
Number of non-workers	0.005	0.016	0.33	0.739	0.005	0.016	0.33	0.738
Number of workers	0.007	0.014	0.53	0.595	0.007	0.014	0.48	0.629
Number of excess jobs	-0.019*	0.019	-1.00	0.317	-0.019*	0.019	-1.00	0.318
Number of children (age < 18)	0.038*	0.010	3.69	<0.001	0.038*	0.010	3.68	<0.001
Number of students	-0.015	0.015	-0.95	0.340	-0.014	0.015	-0.92	0.358
Age of responding adult[b] (categories 1–11)	-0.007*	0.008	-0.90	0.369	-0.007*	0.008	-0.91	0.362
Household income: $50,000-$99,999	0.036	0.026	1.43	0.154	0.037	0.026	1.44	0.149
$100,000-$199,999	0.075	0.032	2.31	0.021	0.077	0.032	2.39	0.017
$200,000 or more	-0.013	0.052	-0.25	0.801	-0.008	0.052	-0.15	0.883
Housing type: Multi-family	0.009	0.030	0.31	0.759	0.010	0.030	0.31	0.754
Housing tenure: Rent	0.008	0.031	0.25	0.801	0.007	0.031	0.22	0.825
Vehicle is an EV	-0.002	0.074	-0.03	0.975	-0.050*	0.065	-0.78	0.435

Sample size (N = 13,963). Goodness-of-fit statistics, BEV: Null model (LL = -33,037), Model 11 (LL = -32,945, McFadden pseudo-R^2 = 0.054), Model 11ab (LL = -32,930, McFadden pseudo-R^2 = 0.054). Goodness-of-fit statistics, BEV/PHEV: Null model (LL = -33,037), Model 12 (LL = -32,947, McFadden pseudo-R^2 = 0.054), Model 12ab (LL = -32,931, McFadden pseudo-R^2 = 0.054).

[a] The coefficient is for the number of household vehicles – 1. [b] The coefficient is for the age category – 4. Difference for rural vs. urban is: * significant (p<0.05), ~ marginally significant (p<0.10).

4.5.2.3 Vehicle Travel Distance

Table 4.11 presents log-linear regression models predicting vehicle trip distance (in miles), estimated across statewide, urban, and rural contexts. In the statewide models (Models 13 and 14), vehicle distances were positively associated with the number of household vehicles. This correlation does not imply that each additional vehicle is driven more; a positive association can arise even if later vehicles are driven less than primary ones and may reflect underlying household travel needs or allocation patterns rather than a per-vehicle increase. The number of non-workers and students were negatively associated with trip distance. Households with older responding adults drive their vehicles slightly shorter distances. Higher household incomes strongly increased vehicle distance, with the largest coefficients observed in the $100,000+ groups. Housing tenure was not significant, but residents of multi-family housing drove their vehicles shorter distances. Rural households traveled slightly shorter distances, but the differences were barely not marginally significant. EV ownership (BEV or BEV/PHEV) did not significantly affect vehicle trip distances statewide.

Comparing the urban models (Models 13a and 14a) with the rural models (Models 13b and 14b), a few significant differences from the statewide results and from each other emerged. The positive effect of vehicle ownership on per-vehicle travel distance was stronger in rural than in urban areas. Conversely, the negative association with the number of non-workers was also stronger for rural than for urban households. Notably, the negative association between number of workers and travel distance per vehicle was not present among urban households, only for rural households. On the other hand, children, students, and the age of the respondent were not significantly linked to vehicle distances traveled in rural areas. The highest-income households (those earning above $200,000) report substantially greater distances, especially in rural areas. Finally, renters in rural areas drove their vehicles shorter distances, but not renters in urban areas. EV ownership (both BEV and BEV/PHEV) was again nonsignificant in both urban and rural models.

Table 4.11: Results of log-linear regression models for vehicle trip distance

Variable	Vehicle is a BEV				Vehicle is a BEV/PHEV			
	Est.	*S.E.*	*z*	*p*	*Est.*	*S.E.*	*z*	*p*
	Model 13: Statewide				**Model 14: Statewide**			
Intercept	3.002	0.040	75.37	<0.001	3.003	0.040	75.36	<0.001
Number of household vehicles[a]	0.056	0.011	4.95	<0.001	0.056	0.011	4.98	<0.001
Number of non-workers	-0.052	0.017	-3.07	0.002	-0.052	0.017	-3.08	0.002
Number of workers	-0.019	0.015	-1.30	0.195	-0.019	0.015	-1.31	0.189
Number of excess jobs	0.030	0.018	1.64	0.101	0.030	0.018	1.64	0.100
Number of children (age < 18)	0.008	0.011	0.73	0.468	0.008	0.011	0.73	0.468
Number of students	-0.049	0.016	-3.05	0.002	-0.049	0.016	-3.04	0.002
Age of responding adult[b] (categories 1–11)	-0.022	0.008	-2.94	0.003	-0.022	0.008	-2.95	0.003
Household income: $50,000-$99,999	0.185	0.025	7.33	<0.001	0.185	0.025	7.34	<0.001
$100,000-$199,999	0.236	0.030	7.82	<0.001	0.237	0.030	7.85	<0.001
$200,000 or more	0.282	0.048	5.92	<0.001	0.284	0.048	5.96	<0.001
Housing type: Multi-family	-0.095	0.029	-3.24	0.001	-0.095	0.029	-3.24	0.001
Housing tenure: Rent	-0.006	0.030	-0.21	0.832	-0.007	0.030	-0.22	0.828
Region: Rural (outside Wasatch Front)	-0.035	0.021	-1.61	0.107	-0.035	0.021	-1.63	0.104
Vehicle is an EV	-0.015	0.059	-0.26	0.798	-0.029	0.052	-0.56	0.577
	Model 13a: Urban				**Model 14a: Urban**			
Intercept	2.979	0.047	63.16	<0.001	2.979	0.047	63.15	<0.001
Number of household vehicles[a]	0.038	0.014	2.65	0.008	0.038	0.014	2.65	0.008
Number of non-workers	-0.025	0.021	-1.18	0.238	-0.025	0.021	-1.18	0.237
Number of workers	0.012	0.018	0.67	0.500	0.012	0.018	0.67	0.504
Number of excess jobs	0.037	0.022	1.72	0.086	0.037	0.022	1.71	0.088
Number of children (age < 18)	0.006	0.014	0.47	0.635	0.007	0.014	0.48	0.630
Number of students	-0.048	0.020	-2.43	0.015	-0.047	0.020	-2.41	0.016
Age of responding adult[b] (categories 1–11)	-0.028	0.009	-3.12	0.002	-0.028	0.009	-3.11	0.002
Household income: $50,000-$99,999	0.154	0.030	5.12	<0.001	0.154	0.030	5.12	<0.001
$100,000-$199,999	0.223	0.035	6.32	<0.001	0.224	0.035	6.32	<0.001
$200,000 or more	0.217	0.056	3.91	<0.001	0.217	0.055	3.91	<0.001
Housing type: Multi-family	-0.095	0.035	-2.75	0.006	-0.095	0.035	-2.75	0.006
Housing tenure: Rent	0.026	0.036	0.72	0.473	0.025	0.036	0.70	0.484
Vehicle is an EV	-0.064	0.066	-0.97	0.332	-0.058	0.059	-0.99	0.323
	Model 13b: Rural				**Model 14b: Rural**			
Intercept	3.026	0.073	41.56	<0.001	3.028	0.073	41.59	<0.001
Number of household vehicles[a]	0.078~	0.019	4.22	<0.001	0.078~	0.019	4.21	<0.001
Number of non-workers	-0.101*	0.030	-3.40	<0.001	-0.101*	0.030	-3.39	<0.001
Number of workers	-0.069*	0.026	-2.70	0.007	-0.070*	0.026	-2.73	0.006
Number of excess jobs	0.024	0.035	0.70	0.486	0.024	0.035	0.69	0.488
Number of children (age < 18)	0.010	0.019	0.51	0.609	0.010	0.019	0.51	0.611
Number of students	-0.038	0.028	-1.35	0.176	-0.037	0.028	-1.32	0.187
Age of responding adult[b] (categories 1–11)	-0.015	0.015	-1.02	0.309	-0.015	0.015	-1.03	0.302
Household income: $50,000-$99,999	0.232	0.047	4.97	<0.001	0.232	0.047	4.97	<0.001
$100,000-$199,999	0.241	0.059	4.07	<0.001	0.244	0.059	4.13	<0.001
$200,000 or more	0.459*	0.094	4.89	<0.001	0.471*	0.093	5.04	<0.001
Housing type: Multi-family	-0.109	0.056	-1.96	0.050	-0.109	0.056	-1.97	0.049
Housing tenure: Rent	-0.104~	0.057	-1.81	0.070	-0.105~	0.057	-1.83	0.067
Vehicle is an EV	0.176	0.135	1.30	0.192	0.072	0.116	0.62	0.535

Sample size (N = 13,963). Goodness-of-fit statistics, BEV: Null model (LL = -21,606), Model 12 (LL = -21,448, McFadden pseudo-R^2 = 0.007), Model 13ab (LL = -21,423, McFadden pseudo-R^2 = 0.008). Goodness-of-fit statistics, BEV/PHEV: Null model (LL = -21,606), Model 14 (LL = -21,448, McFadden pseudo-R^2 = 0.007), Model 14ab (LL = -21,424, McFadden pseudo-R^2 = 0.008).

[a] The coefficient is for the number of household vehicles – 1. [b] The coefficient is for the age category – 4. Difference for rural vs. urban is: * significant (p<0.05), ~ marginally significant (p<0.10).

4.5.2.4 Vehicle Travel Duration

Table 4.12 reports log-linear regression results predicting vehicle trip duration (in minutes), estimated across statewide, urban, and rural contexts. Statewide (Models 15 and 16), the number of household vehicles was not a significant predictor of travel duration. The number of excess jobs, children, and students were all positively associated with vehicle trip duration, whereas the number of workers and non-workers had no significant associations. Older respondent age was significantly associated with longer durations. Household income was positively associated with trip duration, with higher-income households reporting longer driving times per vehicle, particularly those earning above $100,000. Housing type and tenure were not significant. Rural households traveled for shorter durations than urban households. EVs (whether BEV or BEV/PHEV) were not driven for shorter or longer durations, statewide.

When looking at urban households (Models 15a and 16a) and rural households (Model 15b and 16b), separately, several differences emerged. In urban contexts, the number of vehicles was negatively associated with total travel time, and the number of workers and non-workers was positively associated with driving duration. Conversely, in rural areas, the number of non-workers and workers was negatively associated with per-vehicle travel duration, and the number of excess jobs was not a significant factor. Additionally, students and age had positive associations with travel durations in rural areas but not urban areas. On the other hand, renters drove their vehicles for longer (times) among urban households; this factor was not significant in rural areas. In both urban and rural contexts, EVs saw no significant differences in total travel times as compared to ICE vehicles.

Table 4.12: Results of log-linear regression models for vehicle trip duration

Variable	*Est.*	*S.E.*	*z*	*p*	*Est.*	*S.E.*	*z*	*p*
	Vehicle is a BEV				***Vehicle is a BEV/PHEV***			
	Model 15: Statewide				**Model 16: Statewide**			
Intercept	3.884	0.034	115.64	<0.001	3.884	0.034	115.62	<0.001
Number of household vehicles[a]	-0.007	0.009	-0.76	0.447	-0.007	0.009	-0.76	0.450
Number of non-workers	0.005	0.014	0.32	0.746	0.005	0.014	0.32	0.747
Number of workers	0.003	0.012	0.25	0.806	0.003	0.012	0.24	0.810
Number of excess jobs	0.041	0.016	2.62	0.009	0.041	0.016	2.62	0.009
Number of children (age < 18)	0.042	0.009	4.45	<0.001	0.042	0.009	4.45	<0.001
Number of students	0.025	0.014	1.86	0.062	0.025	0.014	1.87	0.062
Age of responding adult[b] (categories 1–11)	0.020	0.006	3.21	0.001	0.020	0.006	3.21	0.001
Household income: \$50,000-\$99,999	0.059	0.021	2.79	0.005	0.059	0.021	2.79	0.005
\$100,000-\$199,999	0.096	0.025	3.78	<0.001	0.096	0.026	3.78	<0.001
\$200,000 or more	0.087	0.040	2.16	0.031	0.087	0.040	2.16	0.031
Housing type: Multi-family	-0.038	0.025	-1.53	0.127	-0.038	0.025	-1.53	0.127
Housing tenure: Rent	0.023	0.025	0.92	0.356	0.023	0.025	0.92	0.358
Region: Rural (outside Wasatch Front)	-0.075	0.018	-4.16	<0.001	-0.075	0.018	-4.16	<0.001
Vehicle is an EV	-0.012	0.050	-0.25	0.805	-0.013	0.044	-0.30	0.762
	Model 15a: Urban				**Model 16a: Urban**			
Intercept	3.868	0.040	97.25	<0.001	3.868	0.040	97.22	<0.001
Number of household vehicles[a]	-0.024	0.012	-2.01	0.045	-0.025	0.012	-2.06	0.040
Number of non-workers	0.044	0.018	2.49	0.013	0.044	0.018	2.51	0.012
Number of workers	0.034	0.015	2.26	0.024	0.035	0.015	2.27	0.023
Number of excess jobs	0.056	0.018	3.07	0.002	0.056	0.018	3.05	0.002
Number of children (age < 18)	0.044	0.011	3.83	<0.001	0.044	0.011	3.84	<0.001
Number of students	0.000	0.017	0.01	0.990	0.000	0.017	0.02	0.985
Age of responding adult[b] (categories 1–11)	0.010	0.007	1.37	0.171	0.010	0.007	1.38	0.167
Household income: \$50,000-\$99,999	0.046	0.025	1.80	0.072	0.045	0.025	1.79	0.074
\$100,000-\$199,999	0.078	0.030	2.60	0.009	0.077	0.030	2.57	0.010
\$200,000 or more	0.073	0.047	1.56	0.119	0.071	0.047	1.52	0.128
Housing type: Multi-family	-0.046	0.029	-1.59	0.111	-0.046	0.029	-1.58	0.113
Housing tenure: Rent	0.051	0.030	1.69	0.090	0.050	0.030	1.68	0.094
Vehicle is an EV	-0.047	0.056	-0.85	0.394	-0.024	0.049	-0.49	0.626
	Model 15b: Rural				**Model 16b: Rural**			
Intercept	3.836	0.061	62.48	<0.001	3.838	0.061	62.51	<0.001
Number of household vehicles[a]	0.017*	0.016	1.08	0.282	0.017*	0.016	1.07	0.286
Number of non-workers	-0.078*	0.025	-3.13	0.002	-0.078*	0.025	-3.13	0.002
Number of workers	-0.054*	0.022	-2.51	0.012	-0.055*	0.022	-2.55	0.011
Number of excess jobs	0.012	0.029	0.40	0.687	0.012	0.029	0.40	0.689
Number of children (age < 18)	0.043	0.016	2.63	0.008	0.043	0.016	2.63	0.009
Number of students	0.086*	0.023	3.65	<0.001	0.087*	0.023	3.69	<0.001
Age of responding adult[b] (categories 1–11)	0.044*	0.012	3.59	<0.001	0.044*	0.012	3.57	<0.001
Household income: \$50,000-\$99,999	0.076	0.039	1.92	0.054	0.076	0.039	1.93	0.053
\$100,000-\$199,999	0.124	0.050	2.49	0.013	0.128	0.050	2.57	0.010
\$200,000 or more	0.102	0.079	1.29	0.197	0.114	0.079	1.44	0.150
Housing type: Multi-family	-0.024	0.047	-0.50	0.614	-0.024	0.047	-0.51	0.613
Housing tenure: Rent	-0.045~	0.048	-0.93	0.353	-0.047~	0.048	-0.96	0.337
Vehicle is an EV	0.122	0.114	1.07	0.284	0.022	0.098	0.23	0.821

Sample size (N = 13,963). Goodness-of-fit statistics, BEV: Null model (LL = -19,111), Model 15 (LL = -19,065, McFadden pseudo-R^2 = 0.002), Model 15ab (LL = -19,043, McFadden pseudo-R^2 = 0.004). Goodness-of-fit statistics, BEV/PHEV: Null model (LL = -19,111), Model 16 (LL = -19,065, McFadden pseudo-R^2 = 0.002), Model 16ab (LL = -19,044, McFadden pseudo-R^2 = 0.004).

[a] The coefficient is for the number of household vehicles – 1. [b] The coefficient is for the age category – 4. Difference for rural vs. urban is: * significant (p<0.05), ~ marginally significant (p<0.10).

4.6 Discussion

This study examined household- and vehicle-level daily travel behavior in Utah, focusing on differences between urban and rural contexts and between EVs and ICE vehicles, and considering different types of EVs (BEVs versus BEV/PHEVs). The results point to mostly expected but some surprising patterns that reveal how demographic, socioeconomic, and geographic factors interact with EV adoption and use.

At the household level, mobility was strongly influenced by household composition and resources. Households with more workers, children, and students were less likely to abstain from travel. Also, while more workers, non-workers, and children in a household tended to generate more trips, greater distances, and longer travel times, the opposite was true for the number of students, which could be consistent with localized school travel or consolidation of activities. Also, these findings reflect the way obligations drive household mobility. In contrast, older respondents and households with more students tended to show lower trip frequency and distance, which may reflect age-related mobility limitations and substitution from student travel. Income also consistently shaped household mobility. Higher-income households traveled more often, farther, and for longer durations, potentially reflecting an income effect: These households were able to “buy” more transportation. Housing characteristics (type, rent versus own) were not consistent predictors of household travel behaviors. In contrast, owning more vehicles reduced the likelihood of not traveling and increased household trip frequencies, travel distances, and travel durations. This might reflect households with greater travel needs having higher vehicle ownership rates. For household travel behavior, significant differences in the relationships between urban and rural areas were rare and not uniform across different outcomes.

At the vehicle level, overall patterns were slightly less consistent than for household travel behaviors. More vehicles in a household increased the likelihood that at least one vehicle did not travel, reflecting substitution when multiple vehicles are available. Statewide, more vehicles in a household decreased per-vehicle trip frequency, increased per-vehicle travel distances, and had no effect on per-vehicle travel durations. Among household composition characteristics, no factors were consistently linked to greater or lesser vehicle use (frequency, distance, and duration), overall and in both urban and rural areas. Although household income was associated with lower likelihood of a vehicle not being used and longer vehicle travel distances and durations (as with household travel), it was not linked to vehicle trip frequencies. Vehicle travel behaviors saw slightly more differences between urban and rural areas, as compared to household travel behaviors. Among the notable differences in rural areas were more positive associations for the number of vehicles and more negative associations for the number of non-workers and workers, for both vehicle travel distances and durations. In other words, having more vehicles increased vehicle distances more (and decreased vehicle durations less) among rural households, while having more household members of working age (whether working or not) decreased vehicle distances and durations in rural areas. Although we are uncertain about the reasons for these geographic differences, they may reflect a combination of longer distances but higher speeds and less congestion in rural areas, as well as different expectations and capabilities for carpooling or trip chaining in rural versus urban areas.

We turn now to the focus of this study: EVs, their relationships with household and vehicle travel behaviors, and any differences in urban and rural areas. Importantly, EV ownership itself did not significantly alter household-level travel behaviors: traveling at all, trip frequency, travel distance, or travel duration. The only notable difference was that urban households with a BEV or PHEV were more likely to travel, whereas EV ownership did not affect rural households' choice to travel or not. Overall, this implies that, once demographic and socioeconomic factors were considered, EV-owning households behaved similarly to non-EV households in their daily mobility, at least at a household level.

On the other hand, investigation of travel behaviors at the vehicle level revealed a few notable differences for EVs. Most notably, EVs were less likely to remain unused than ICE vehicles, but only in urban areas. This suggests that EVs are actively incorporated into urban households' daily travel rather than serving as backup cars for special trips. In contrast, ICE vehicles might be more likely to be these households' second vehicles. In contrast, rural residents with EVs do not seem to be making this kind of decision about what vehicle to use. Additionally, urban EVs showed higher trip frequencies compared to non-EVs, while rural EVs did not differ significantly from ICE vehicles. For vehicle distances and durations, EVs were used neither more nor less than ICE vehicles, in both urban and rural areas. This pattern suggests that EVs in urban areas may be being used more for short, frequent daily urban trips; whereas rural travel patterns, which involve longer distances and less charging availability, minimize differences in use between EVs and non-EVs.

Taken together, the results indicate that demographic and socioeconomic characteristics remain the dominant drivers of travel behavior, in both urban and rural areas, while EV ownership plays a secondary role. At the household level, EVs do not change whether or how much households travel. At the vehicle level, however, EVs appear somewhat more actively used, especially in urban contexts. These results could reflect deliberate reasoned decisions among EV owners, who may only invest if an EV fits within their lifestyle. Yet the results also indicate that EVs and EV-owning households are largely able to maintain similar travel amounts as non-EVs and non-EV-owning households. This could suggest that range anxiety is less a practical barrier than a perceived barrier, or that households are able to implement strategies to manage their daily charging needs without sacrificing mobility.

These findings have several implications for transportation planning. Overall, EV adoption does not appear to reduce household mobility; instead, EVs are integrated into existing routines, particularly in urban areas. In rural contexts, EVs are used comparably to non-EVs but without evidence of higher utilization, pointing to range and infrastructure limitations. If future EV owners, households, and drivers make travel decisions and use EVs in similar ways as current EV owners do, then any overall travel behavior changes (more/fewer trips, longer/shorter durations and distances) due to transportation electrification may be relatively minor. Income plays a strong role across all models, with higher-income households consistently traveling more frequently, farther, and for longer durations. This underscores persistent income-related disparities in mobility and access, which relates to the benefits and barriers of EV adoption (Soltani Mandolakani & Singleton, in preparation). Rural households, especially those with lower incomes or older respondents, face reduced mobility overall, raising concerns about geographic inequities in access to opportunities and the benefits of electrification.

In summary, EV ownership does not appear to be fundamentally reshaping household travel behavior. But electrification does appear to somewhat influence vehicle-level utilization, particularly daily use as well as trip-making, at least in urban areas. Policies should therefore focus not only on expanding EV adoption but also on addressing the barriers faced by rural and lower-income households, including infrastructure access and affordability, to ensure that EVs contribute meaningfully to mobility across all communities.

4.7 Conclusions

This study provides a systematic analysis of daily travel behavior among electric vehicle households in Utah (as of 2023), distinguishing between urban and rural contexts. Using detailed household travel survey data, we found that demographic and socioeconomic characteristics such as vehicle availability, household structure, income, and respondent age remain the strongest determinants of travel participation, trip frequency, and overall travel distance and duration. In contrast, EV ownership itself does not significantly alter daily household travel outcomes once these household factors are accounted for. EVs may be less likely to remain unused and may make more trips per day (in urban but not rural areas), but those differences disappear when looking at household-level person–travel overall.

Spatial context, however, can amplify some differences in travel behavior. Overall, most rural–urban differences in trip frequency, distance, and duration were not statistically significant. However, rural households demonstrated more pronounced income effects, with higher-income rural households traveling substantially more than their lower-income counterparts. These findings suggest that while EV ownership may not yet drive measurable differences in travel patterns, the built environment and socioeconomic conditions can modestly shape mobility outcomes across regions.

For policymakers and planners, the results highlight the importance of tailoring EV-supportive strategies to the realities of local contexts. In rural areas, improving charging infrastructure and supporting mobility for older and lower income households could reduce disparities in travel opportunities. In urban settings, because higher-income households in our sample travel more often, farther, and longer, EV policy should pair broad incentives with targeted measures—e.g., multifamily/curbside charging grants in lower-income neighborhoods, point-of-sale rebates for used EVs with affordable financing, and time-of-use or on-bill credits—so adoption and charging access can expand without widening income-based differences in mobility. Future research should continue to track changes as EV adoption expands, battery ranges increase, and infrastructure networks mature, to assess whether travel behavioral differences between EV and non-EV households become more pronounced over time.

4.8 Acknowledgments

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5.0 CHARGING BEHAVIORS OF EV USERS IN URBAN AND RURAL UTAH

5.1 Abstract

Electric vehicle (EV) adoption is increasing rapidly, creating a need to better understand where and when EV users charge their vehicles. This study analyzes EV charging behavior in Utah using data from the 2023 Utah Moves Household Travel Survey; EVs included battery-electric and plug-in hybrid EVs. Three related outcomes are examined: charger presence at up to 4,233 trip destinations, charging at the end of up to 1,639 trips with chargers, and household charging at home at the end of the day (for 873 household-days). Binomial logistic regression models are estimated for trip-level and household-day-level data, with comparisons between urban and rural trips and households. Results show that charger availability is strongly associated with destination type, with home and work destinations having the highest odds of charger presence. Rural destinations have moderately higher odds of charger availability than urban destinations. When a charger is present, charging is most likely at work destinations, and rural users are more likely than urban users to charge at trip destinations. Distance traveled since the previous charge is associated with charger presence and with charging behavior for rural trips but not for urban trips. Layover duration is positively associated with charging in urban areas but not or negatively associated with charging in rural areas. Household models indicate that multi-EV households and renting households are more likely to charge at home, and that greater access to public EV charging may slightly decrease the odds of charging at home. Overall, the results suggest that EV charging behavior reflects both necessity-driven and opportunity-driven decisions, with rural users relying more on distance-based strategic destination charging and urban users relying more on opportunistic charging.

5.2 Introduction

Electric vehicle (EV) adoption has accelerated in recent years, driven by advances in technology, declining costs, and growing public and private investments in charging infrastructure (Coffman et al., 2015; Hardman et al., 2016). This growth has significant implications for transportation planning and utility management, particularly as charging needs and behaviors vary across different communities. For instance, EV registrations in Utah have risen rapidly—from 1.1% in 2015 to 4.3% in 2024 (Paskett & Singleton, in preparation)—reflecting both market shifts and state-level efforts to promote cleaner transportation. As adoption accelerates, understanding where and when EV users choose to charge their vehicles is essential for transportation planners, utilities, and policymakers tasked with ensuring that charging infrastructure investments align with actual user behavior.

Urban and rural regions face distinct opportunities and challenges. Urban areas typically offer denser networks of public and workplace chargers, shorter average trip lengths, and greater diversity in housing types (Illmann & Kluge, 2020). In contrast, rural areas often feature longer trip distances, fewer charging opportunities, and a higher prevalence of single-family residences. People with EVs living in certain types of housing may be less likely or able to charge at home and thus may rely more on public charging (Illmann & Kluge, 2020). Understanding how these factors shape EV charging behaviors is critical for developing policies and infrastructure investments that support efficient and reliable access to EV charging, whether at home or in public.

In this report, we examine the charging behaviors of EV users, seeking to describe and explain them, and comparing these charging behaviors across urban and rural areas. Our analysis focuses on three key decisions: (1) whether a charger is present at the end of a trip (a proxy for whether charging affects destination choices), (2) whether the user chooses to charge their vehicle at the end of that trip, and (3) whether a household member charges a vehicle at home at the end of the day. We study Utah using data from the 2023 Utah Moves Household Travel Survey. By examining these decisions across both urban and rural contexts, this study provides actionable insights to guide infrastructure planning, utility coordination, and policy development to better meet the needs of EV users statewide.

5.2.1 Literature Review

Built environment characteristics are a fundamental driver of charging opportunities and behavior. Public charger density, land use context, and typical dwell times at destinations strongly influence whether charging is feasible during a trip (Borlaug et al., 2020; Nicholas et al., 2013). Studies show that users are far more likely to charge in locations with predictable access—such as workplaces, shopping centers, or long-duration activity locations—while areas with sparse infrastructure limit opportunities and can increase range-related anxiety (Figenbaum & Kolbenstvedt, 2016). The regional context also plays a critical role: Urban regions generally offer more abundant chargers, whereas rural regions have fewer facilities, often far apart, forcing users to incorporate charging more strategically into their daily activity patterns.

User-based factors, including trip length, daily travel requirements, and vehicle state of charge (SoC), additionally influence when charging is necessary or advantageous. Studies using real-world charging logs and travel diary data have found that users tend to charge when their SoC is low, after long trips, or before anticipated long trips (Xi et al., 2013). Longer layovers, especially at home or at work, significantly increase the probability of charging (Illmann & Kluge, 2020). Household characteristics also shape behavior. Access to home charging remains the dominant predictor of charging patterns, but access is uneven: Renters and residents of multifamily housing face structural barriers that reduce their ability to charge at home (Coffman et al., 2015).

5.2.2 Conceptual Framework

Based on this brief literature review, we constructed visual models to capture the hypothesized relationships leading to the EV charging behaviors analyzed in this report. Figure 5.1 illustrates a conceptual framework of related factors influencing whether an EV user may decide to charge their vehicle at the end of a trip. Factors in orange indicate attributes that were not influenced by the EV user, including characteristics of the built environment and other EV users. Factors in blue are attributes directly influenced by the user's behavior, such as data related to SoC, charger accessibility, and trip purpose. Elements in green are decisions made by the user. Oval nodes represent factors directly related to the presence of an EV charger. The two highlighted factors—charger present at destination and charge decision—represent two of the decisions that are modeled in this study.

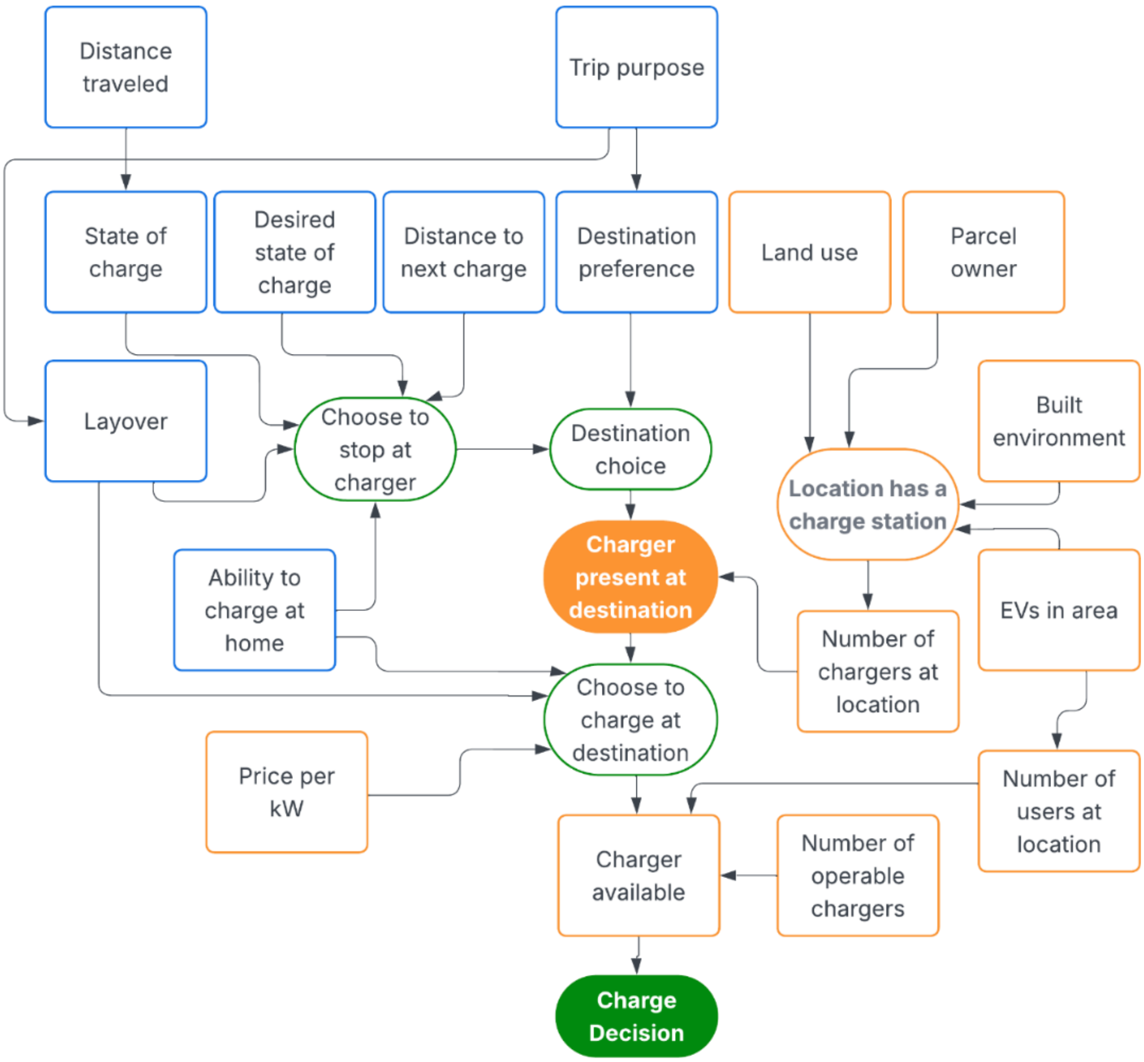

Figure 5.1: Hypothesized factors affecting EV charging at the end of a trip

The conceptual framework in Figure 5.2 shows factors we believe to be influential in affecting whether a household chooses to charge their (or one of their) EVs at home at the end of the day. A similar set of user or user behavior characteristics are shown in blue, while the built environment factors (orange) are represented as a single region variable.

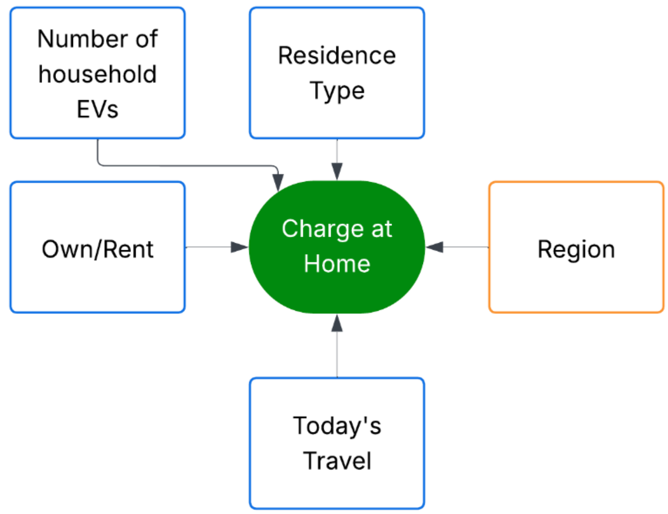

Figure 5.2: Hypothesized factors affecting EV charging at the end of a day

5.3 Data and Methods

Most data for this study come from the 2023 Utah Moves Household Travel Survey (HTS), obtained from the Wasatch Front Regional Council. This dataset included four primary EV charging behavior variables, taken from questions asked of EV users, with either battery-electric vehicles (BEVs) or plug-in hybrid electric vehicles (PHEVs). The first question asked whether any user in a household charged any of the household's EVs at the end of each day; this is defined only for days and only for households as a whole, so it is not known whether a particular EV was plugged in at day's end. For EV trips, there were three charging-related questions. The first asked whether a charging station was present at the end of a user's journey and (if so) whether they charged their vehicle at it. Another question asked what levels of charging stations were present at the destination (level 1, 2, or 3). The last question asked whether the presence of a charging station played a role in the user's choice to stop at that destination. Of these four total EV charging behavior questions, only the end-of-day charging question and the two-part end-of-trip charging question were selected for analysis in this study. Based on the literature review (and as shown in our conceptual diagram), we assumed that the level of the destination's charging station did not have a direct effect on the decision to charge, so this question was not included in the analysis. Although the question asking whether a user chose the destination in part due to the presence of a charging station was interesting, this question was only answered for 191 trips, so we determined that an analysis of this question would not yield meaningful or generalizable results.

Based on the data available within the HTS, the conceptual framework shown in Figure 5.1 was simplified to match the available data, with proxy variables being selected to simulate the effects of various factors on the modeled results. This revised trip-charging framework is shown in Figure 5.3. (There was no need to simplify the day-charging conceptual framework shown in Figure 5.2 to address data limitations.) The HTS does not contain relevant data for the built environment, and so destination region, either urban or rural, defined later, was selected as a proxy for this information on the logic that region and the built environment are generally related. The state-of-charge of each EV was not known; instead, we calculated the distance since the vehicle's last charging event (an EV that has traveled farther will have a lower SoC), assuming all vehicles started the survey with a full charge. Additionally, whether the vehicle was charged at home the previous night or would be charged that night is included, as that may influence the need to charge during the day.

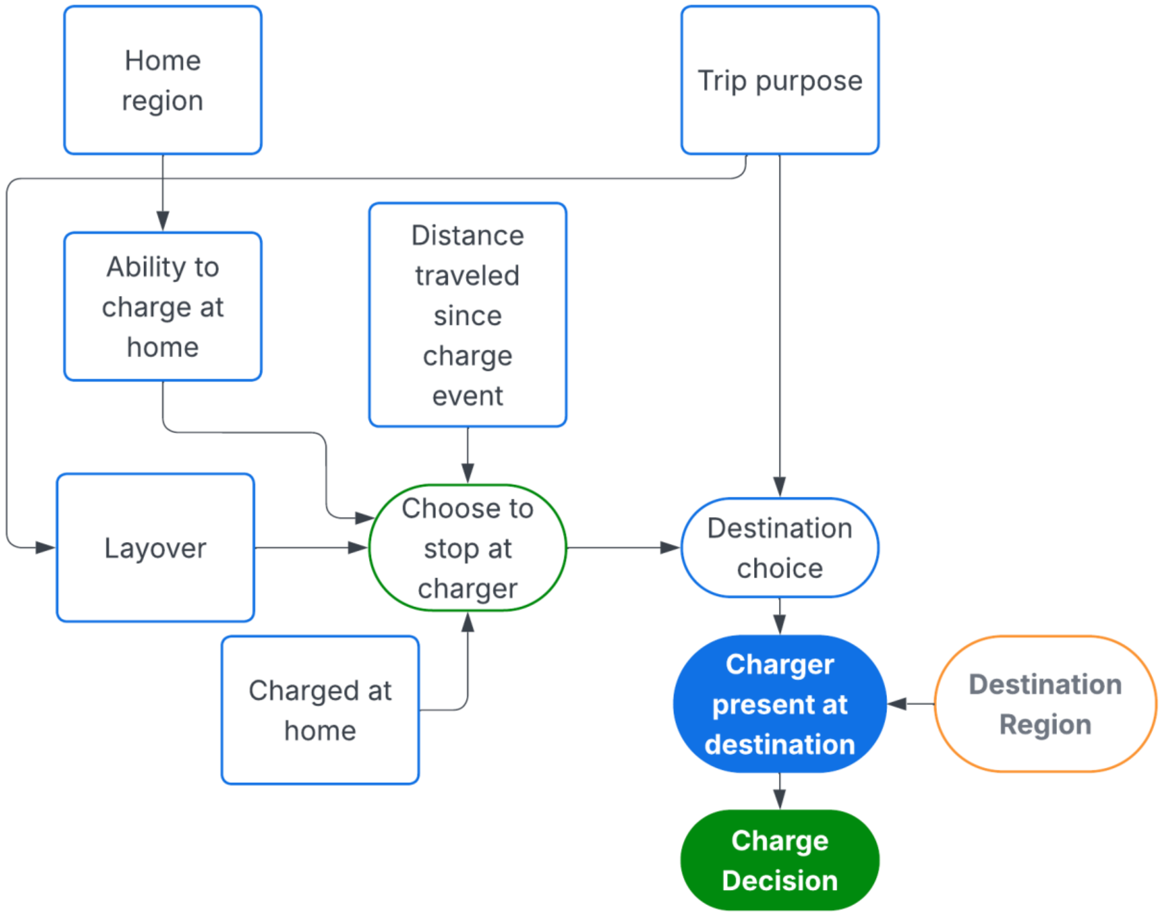

Figure 5.3: Revised factors affecting EV charging at the end of a trip

Data were obtained from the HTS, specifically the trip, person, day, and household tables. These datasets were joined using household, person, and day identifiers to create a trip table containing trip characteristics (e.g., origin and destination, purpose, distance, and dwell time), household and vehicle attributes (e.g., number of EVs per household, region, residential type), and daily charging and travel information. Additional variables were derived from the available data. This included the distance a vehicle traveled since its previous charging event and the total distance a vehicle traveled over the course of a day. Each trip was classified by its destination region, urban or rural, and each household by its home region. For the purposes of this work (and given limited numbers of EVs among rural households), an area was designated as "urban" if it fell within the boundaries of the Wasatch Front Regional Council or

Mountainland Association of Governments (effectively the largest continuous urbanized area in Utah, from Ogden to Provo, including Salt Lake City), and "rural" for all other parts of the state.

To compile the day table for each household, the region, number of household EVs, and residence type information was linked to each household based on their responses to the HTS. Because the number of households with more than two EVs was small (only 63), the number of household EVs was transformed into a binary variable representing whether the household had two or more EVs. The question of whether a vehicle was charged at the end of the day was answered by any member of the household for any vehicle in the household. There is no way to model this per individual vehicle. As such, for multi-EV households, we determined the longest distance traveled by any household EV for each day to model household daily travel.

Table 5.1 shows the variables used in the trip-based models (N = 4,233 and 1,639), along with their descriptive statistics. Table 5.2 shows the variables used in the day-based models (N = 873), along with their descriptive statistics. For the trip data analysis, the variable "Charged at home today or yesterday" is included to help minimize data lost when accounting for the first or last days in the dataset for a given household. For the day data analysis, the max vehicle distance variables indicate the maximum distance traveled by any household EV that day, in the case that a household had more than one EV. The number of EVs includes both BEVs and PHEVs; although a large majority were BEVs. Access to public EV charging indicates the availability of public EV chargers around the household's location. This metric incorporates various demographic, geographic, and transportation factors, and was calculated by other authors (Soltani & Singleton, in preparation).

To examine charging behavior, a series of binomial logistic regression models were estimated to examine each decision variable: (1) whether a charger was present at the end of a trip, (2) whether the user charged their vehicle at the end of a trip, and (3) whether a household member charged a household EV at the end of a day. For the trip-based variables, two model variations were created, one including trips that ended at home, and one that did not. This was done to examine the effects of trips returning home, which may be much more likely to have charging events, compared to trips to other non-home destinations. Because whether a user charged at home is highly correlated with trips that end at home, this destination purpose level was excluded from those models, making work the reference category. Each model included three variants: a statewide pooled model of all trips, and separate (a) urban and (b) rural models to examine the differences between charging behaviors in different parts of Utah.

Table 5.1: Descriptive statistics of trip data

	Categorical		*Continuous*		
Variable	*#*	*%*	*Mean*	*SD*	*10th, 50th, 90th percentiles*
Dependent variables					
Charge station is present (*N* = 4,233*)*					
True	1,639	38.7			
False	2,594	61.3			
Vehicle is charged (*N* = 1,639)					
True	786	48.0			
False	853	52.0			
Independent variables (charge station is present) (*N* = 4,233)					
Distance (miles) since last charge			26.90	31.80	2.49, 16.26, 66.31
Charged at home today or yesterday: True	3,456	81.6			
False	777	18.4			
Destination purpose: Home	1,282	30.3			
Work	482	11.4			
Shop	369	8.7			
Personal business	216	5.1			
Other	1,374	32.5			
Missing response	510	12.0			
Layover (minutes)			236.49	418.36	0.00, 49.32, 779.94
Destination region: Urban	3,367	79.5			
Rural	866	20.5			
Independent variables (vehicle is charged) (*N* = 1,639)					
Charged at home today or yesterday: True	1,316	80.3			
False	323	19.7			
Distance (miles) since last charge			30.93	36.71	3.26, 18.45, 75.07
Destination purpose: Home	978	59.7			
Work	176	10.7			
Shop	35	2.1			
Personal business	21	1.3			
Other	242	14.8			
Missing response	187	11.4			
Layover (minutes)			416.55	532.26	0.00, 218.53, 1016.98
Destination region: Urban	1,256	76.6			
Rural	383	23.4			

Table 5.2: Descriptive statistics of day data

Variable	Categorical #	Categorical %	Continuous Mean	Continuous SD	10th, 50th, 90th percentiles
Dependent variable					
Charged at home: True	598	68.5			
False	275	31.5			
Independent variables					
Max distance (miles) since last charge			30.01	35.14	0.00, 18.45, 74.11
Number of EVs (#)			1.19	0.41	1, 1, 2
Housing type: Single-family	835	95.6			
Multi-family	38	4.4			
Housing tenure: Own	822	94.2			
Rent	51	5.8			
Access to public EV charging			57.47	40.45	7.29, 55.20, 118.39
Household region: Urban	670	76.7			
Rural	203	23.3			

5.4 Results

5.4.1 Trip-Level Charging Data

Table 5.3 and Table 5.4 present the results for the binomial logistic regression models for whether a charger was present at the trip destination (Models 1 and 2, Table 5.3) and whether the user charged their vehicle at the destination (Models 3 and 4, Table 5.4). Each table shows the results of the pooled statewide model (Model X), as well as the results of the interacted model, split into the results for the urban (Model Xa) and rural (Model Xb) sections. Predictors with a significant difference in value between the urban and rural regions are marked in the rural section of the table.

Table 5.3: Results of logistic regression models for whether a charger is present

	Including home trips				*Excluding home trips*			
Variable	***Est.***	***S.E.***	***z***	***p***	***Est.***	***S.E.***	***z***	***p***
	Model 1: Statewide				**Model 2: Statewide**			
Intercept	0.196	0.154	1.28	0.202	-1.133	0.206	-5.51	<0.001
Charged at home today or yesterday	--	--	--	--	-0.330	0.117	-2.82	0.005
Distance[a] since last charge	0.177	0.035	5.09	<0.001	0.209	0.042	4.94	<0.001
Destination purpose: Work	-1.620	0.119	-13.62	<0.001	--	--	--	--
Shop	-3.226	0.197	-16.40	<0.001	-1.639	0.205	-8.01	<0.001
Personal business	-3.160	0.245	-12.91	<0.001	-1.564	0.251	-6.22	<0.001
Other	-2.519	0.110	-22.94	<0.001	-0.924	0.123	-7.50	<0.001
Missing response	-1.673	0.117	-14.24	<0.001	0.000	0.135	0.000	0.997
Layover[b]	0.074	0.019	3.92	<0.001	0.047	0.022	2.15	0.032
Destination region: Rural	0.442	0.092	4.80	<0.001	0.328	0.108	3.04	0.002
	Model 1a: Urban				**Model 2a: Urban**			
Intercept	0.029	0.173	0.17	0.865	-1.079	0.238	-4.53	<0.001
Charged at home today or yesterday	--	--	--	--	-0.632	0.136	-4.66	<0.001
Distance[a] since last charge	0.142	0.040	3.58	<0.001	0.156	0.050	3.16	0.002
Destination purpose: Work	-1.588	0.132	-12.03	<0.001	--	--	--	--
Shop	-3.037	0.221	-13.72	<0.001	-1.451	0.236	-6.15	<0.001
Personal business	-3.193	0.293	-10.91	<0.001	-1.567	0.304	-5.15	<0.001
Other	-2.377	0.123	-19.37	<0.001	-0.771	0.147	-5.25	<0.001
Missing response	-1.375	0.132	-10.42	<0.001	0.346	0.159	2.18	0.029
Layover[b]	0.116	0.022	5.31	<0.001	0.101	0.026	3.83	<0.001
	Model 1b: Rural				**Model 2b: Rural**			
Intercept	1.441*	0.356	4.04	<0.001	-1.217	0.400	-3.04	0.002
Charged at home today or yesterday	--	--	--	--	0.389*	0.245	1.59	0.112
Distance[a] since last charge	0.268	0.075	3.59	<0.001	0.367*	0.086	4.30	<0.001
Destination purpose: Work	-2.115	0.302	-7.01	<0.001	--	--	--	--
Shop	-4.000~	0.440	-9.10	<0.001	-1.914	0.432	-4.43	<0.001
Personal business	-3.276	0.484	-6.77	<0.001	-1.110	0.476	-2.33	0.020
Other	-3.160*	0.267	-11.85	<0.001	-1.082	0.250	-4.33	<0.001
Missing response	-2.706*	0.276	-9.79	<0.001	-0.619*	0.281	-2.20	0.028
Layover[b]	-0.066*	0.041	-1.61	0.108	-0.072*	0.045	-1.59	0.111

Sample size, including home trips (N = 4,233). Goodness-of-fit statistics, including home trips: Null model (LL = -2,825), Model 1 (LL = -2,146, McFadden pseudo-R^2 = 0.240), Model 1ab (LL = -2,129, McFadden pseudo-R^2 = 0.247).

Sample size, excluding home trips (N = 2,951). Goodness-of-fit statistics, excluding home trips: Null model (LL = -1,570), Model 1 (LL = -1,451, McFadden pseudo-R^2 = 0.076), Model 1ab (LL = -1,428, McFadden pseudo-R^2 = 0.090).

[a] Distance is modeled as the natural logarithm of miles. [b] Layover duration is modeled as the natural logarithm of minutes. -- Variable/category not included in model. Difference for rural vs. urban is: * statistically significant (p < 0.05), ~ marginally significant (p < 0.10).

Table 5.3 presents the results of the logistic regression models predicting whether a charger is present at trip destinations. Charging at home was significantly associated with charger presence when excluding home trips (Model 2). Statewide, there were 28% lower odds of having a charger present when users charged at home the same day or the previous day. Urban trips had approximately 47% lower odds of charger presence if they charged at home, while this variable was not statistically significant for rural trips.

A greater distance traveled since the previous charge was associated with higher odds of charger presence at the destination. In the statewide models, each additional 1% of distance traveled since the previous charge corresponds to approximately 0.18–0.21% higher odds of charger presence depending on whether home trips were included (Model 1) or excluded (Model 2). This positive relationship was also observed for both urban and rural trips, with increases of approximately 0.14–0.16% and 0.27–0.37% in the odds of charger presence per additional 1% distance traveled, respectively, depending on whether home trips were included.

Destination purpose was also significantly associated with charger presence. Relative to trips ending at home, all other destination types were much less likely to have a charger present. In the statewide model, shopping and personal business destinations were the least likely to have a charger present, with approximately 96% lower odds than home destinations. Work destinations were more likely to have a charger present, but the odds were still only 20% of the odds (80% lower odds) of having a charger at home. Among urban trips, personal business destinations had the lowest odds of charger availability (approximately 96% lower than home), while for rural trips shopping destinations had approximately 98% lower odds than home. Similar patterns were observed when comparing non-home destinations (Model 2), where work destinations had significantly higher odds of charger availability than other non-home destination types.

Layover duration was also significantly associated with charger presence in the statewide and urban models. Longer layovers (by 1%) were associated with 0.05–0.07% higher odds of charger presence in the statewide model, and 0.10–0.12% for urban users, depending on whether home trips were excluded or included. Layover duration was not a statistically significant predictor in the rural models.

Destination region was a significant predictor in both statewide models. Rural destinations had higher odds of charger availability than urban destinations. When excluding trips that end at home, rural destinations have approximately 39% higher odds of charger presence than urban destinations; this increases to 56% higher odds when including home trips.

There were also several significant differences in influential factors for rural versus urban trips. For non-home trips, charging at home was almost a significant and positive influence on having a charger at the destination, whereas it was a negative and significant factor for urban trips. The positive effect of distance traveled on charger presence was significantly weaker for rural non-home trips than for urban non-home trips. Finally, whether including or excluding home trips, layover duration had a nearly significant negative effect on charger presence for rural trips, whereas layover was a significant and positive factor for urban trips.

Overall, charger presence at destinations was most strongly associated with destination type, with home and work destinations having the highest odds of charger presence. Distance traveled since the previous charge and layover duration were also consistent predictors with positive associations; however, their effects were weaker or nearly negative for rural trips as compared with urban trips. Rural trips were more likely to have a charger at the destination; and the roles of charging at home, distance since the last charge, and layover time were somewhat different for rural trips, which might explain the overall finding.

Table 5.4: Results of logistic regression models for whether an EV was charged

	Including home trips				*Excluding home trips*			
Variable	*Est.*	*S.E.*	*z*	*p*	*Est.*	*S.E.*	*z*	*p*
	Model 3: Statewide				**Model 4: Statewide**			
Intercept	-0.843	0.204	-4.12	<0.001	-0.426	0.336	-1.27	0.205
Charged at home today or yesterday	--	--	--	--	0.566	0.205	2.76	0.006
Distance[a] since last charge	0.053	0.046	1.15	0.251	0.100	0.074	1.34	0.180
Destination purpose: Work	0.759	0.174	4.37	<0.001	--	--	--	--
Shop	0.042	0.363	0.12	0.908	-0.887	0.395	-2.24	0.025
Personal business	-0.531	0.494	-1.08	0.282	-1.517	0.519	-2.92	0.003
Other	0.498	0.169	2.94	0.003	-0.484	0.218	-2.22	0.026
Missing response	0.222	0.162	1.37	0.171	-0.647	0.231	-2.80	0.005
Layover[b]	0.080	0.026	3.09	0.002	0.009	0.036	0.24	0.807
Destination region: Rural	0.242	0.118	2.05	0.041	0.781	0.190	4.12	<0.001
	Model 3a: Urban				**Model 4a: Urban**			
Intercept	-0.917	0.240	-3.82	<0.001	-0.742	0.404	-1.84	0.066
Charged at home today or yesterday	--	--	--	--	0.697	0.239	2.91	0.004
Distance[a] since last charge	-0.016	0.054	-0.30	0.765	0.028	0.089	0.31	0.757
Destination purpose: Work	0.334	0.195	1.72	0.086	--	--	--	--
Shop	-0.234	0.442	-0.53	0.597	-0.816	0.474	-1.72	0.086
Personal business	-0.033	0.574	-0.06	0.954	-0.680	0.599	-1.14	0.256
Other	0.502	0.200	2.51	0.012	-0.171	0.263	-0.65	0.515
Missing response	0.183	0.186	0.99	0.324	-0.407	0.263	-1.55	0.121
Layover[b]	0.148	0.031	4.74	<0.001	0.069	0.042	1.65	0.099
	Model 3b: Rural				**Model 4b: Rural**			
Intercept	-1.188	0.449	-2.65	0.008	1.666*	0.711	2.34	0.019
Charged at home today or yesterday	--	--	--	--	-0.325~	0.476	-0.68	0.495
Distance[a] since last charge	0.332*	0.102	3.24	0.001	0.342~	0.156	2.19	0.028
Destination purpose: Work	2.302*	0.494	4.66	<0.001	--	--	--	--
Shop	1.172	0.858	1.37	0.172	-1.099	0.952	-1.15	0.248
Personal business	-1.279	1.106	-1.16	0.248	-3.558*	1.169	-3.04	0.002
Other	0.719	0.352	2.04	0.041	-1.598*	0.520	-3.07	0.002
Missing response	0.497	0.350	1.42	0.155	-1.399	0.582	-2.40	0.016
Layover[b]	-0.024*	0.056	-0.43	0.670	-0.168*	0.083	-2.01	0.044

Sample size, including home trips (N = 1,639). Goodness-of-fit statistics, including home trips: Null model (LL = -1,135), Model 3 (LL = -1,117, McFadden pseudo-R^2 = 0.015), Model 3ab (LL = -1,091, McFadden pseudo-R^2 = 0.038).
Sample size, excluding home trips (N = 661). Goodness-of-fit statistics, excluding home trips: Null model (LL = -458), Model 4 (LL = -437, McFadden pseudo-R^2 = 0.044), Model 4ab (LL = -426, McFadden pseudo-R^2 = 0.069).
[a] Distance is modeled as the natural logarithm of miles. [b] Layover duration is modeled as the natural logarithm of minutes. -- Variable/category not included in model. Difference for rural vs. urban is: * statistically significant ($p < 0.05$), ~ marginally significant ($p < 0.10$).

Table 5.4 presents the results of the logistic regression models predicting whether an EV was charged at the end of a trip. Charging behavior at home was significantly associated with destination charging in Model 4. Statewide, users who charged at home the same day or the previous day had approximately 76% higher odds of charging at the end of a trip than users who did not charge at home. Overall, EV users who had driven further distance since their last charge were no more or less likely to charge at their trip's destination; however, this effect was significant and positive for rural trips.

In the statewide model including trips that end at home (Model 3), some destination purposes were significantly associated with charging behavior. Relative to home destinations, trips ending at work had approximately 114% higher odds of charging, while trips classified as "other" destinations had approximately 65% higher odds of charging. When excluding trips ending at home (Model 4), trips ending at work had higher odds of charging than trips to other destination types. Shopping, personal business, "other," and missing-response destinations all had significantly lower odds of charging than work destinations, with reductions in the odds of charging ranging from approximately 38% to 78%.

Layover duration was positively associated with charging when including trips that end at home, where a 1% longer layover time corresponded to approximately 0.08% higher odds of charging. However, layover duration was not a significant predictor when excluding home trips. Destination region was also a significant predictor in both statewide models. Rural trip destinations had higher odds of charging than urban destinations, with approximately 27% higher odds when including home trips and approximately 118% higher odds when excluding home trips. There appear to be significant urban/rural differences in charging behavior.

Results from the urban-only models (Models 3a and 4a) showed significant relationships that were largely similar to those in the statewide models. Urban trips for EV users who charged at home the same day or the previous day had approximately 101% higher odds of charging at trip destinations when home trips are excluded. Distance since the last charge was not an influential factor for urban trips. When including home trips, trips classified as having work or "other" destinations had significantly higher odds of charging than home destinations (40% and 65%, respectively). Layover duration was significant for all urban trips: a 1% increase in layover duration was associated with 0.07–0.15% greater odds of charging at the destination.

The rural models (Models 3b and 4b) showed some significant differences in associations with charging at trip destinations. Charging at home was not related to charging at non-home rural trip destinations. Instead, distance traveled since the last charge was a positive and significant factor: A 1% increase in distance was linked to about 0.33–0.34% higher odds of charging at the end of a rural trip. The destination purpose also had a stronger effect for rural trips than for urban trips: The odds of charging were more than nine times higher at work than at home. Finally, the only instance when layover duration was significant was for non-home rural trips, where a 1% increase in layover duration was linked to a 0.17% lower (not higher, as for urban trips) odds of charging. Overall, rural charging behavior was more strongly associated with destination purpose and travel distance than urban charging behavior.

5.4.2 Household Day-Level Charging Data

Table 5.5 presents the results for the binomial logistic regression models for whether a household member charged an EV at home at the end of a day. It shows the results of the pooled statewide model (Model 5), as well as the results of the interacted model, split into the results for the urban (Model 5a) and rural (Model 5b) portions. Predictors with a significant difference in value between the urban and rural region are marked in the rural section of the table (there were none).

Table 5.5: Results of logistic regression models for whether an EV was charged at home

Coefficient	*Est.*	*S.E.*	*z*	*p*
	Model 5: Statewide			
Intercept	0.961	0.237	4.06	<0.001
Max distance[a] since last charge	-0.024	0.052	-0.46	0.645
Number of EVs: 2 or more	0.675	0.212	3.18	0.001
Housing type: Multi-family	0.318	0.457	0.70	0.487
Housing tenure: Rent	1.148	0.448	2.56	0.010
Access to public EV charging	-0.004	0.002	-1.68	0.092
Household region: Rural	-0.245	0.230	-1.06	0.288
	Model 5a: Urban			
Intercept	1.040	0.251	4.15	<0.001
Max distance[a] since last charge	-0.035	0.061	-0.57	0.566
Number of EVs: 2 or more	0.567	0.239	2.37	0.018
Housing type: Multi-family	0.175	0.470	0.37	0.710
Housing tenure: Rent	1.198	0.454	2.64	0.008
Access to public EV charging	-0.005	0.002	-1.85	0.065
	Model 5b: Rural			
Intercept	0.314	0.373	0.84	0.400
Max distance[a] since last charge	0.024	0.107	0.23	0.882
Number of EVs: 2 or more	1.013	0.484	2.09	0.036
Housing type: Multi-family	--	--	--	--
Housing tenure: Rent	--	--	--	--
Access to public EV charging	0.020	0.019	1.07	0.283

Sample size (N = 873). Goodness-of-fit statistics: Null model (LL = -544), Model 5 (LL = -532, McFadden pseudo-R^2 = 0.022), Model 5ab (LL = -531, McFadden pseudo-R^2 = 0.024).
[a] Distance is modeled as the natural logarithm of miles. -- Variable/category not included in model. Difference for rural vs. urban is: * statistically significant ($p < 0.05$), ~ marginally significant ($p < 0.10$).

In the statewide model (Model 5), only housing tenure, the number of household EVs, and access to public charging were significantly associated with charging at the end of the day. Households were 215% more likely to charge at the end of the day if they were renting than owning their home, and 96% more likely to charge an EV if the household owned two or more EVs. They were slightly less likely to charge at the end of the day if they had easier access to a public charger. Rural households may have been less likely to charge at home, but the effect was not statistically significant.

Results for urban households largely matched those of the statewide model. For rural households, the only significant factor was a 175% increase in odds of charging at home if the household had two or more EVs. However, this and all other parameters were not significantly different between urban and rural households. Due to the small number of households renting or in multi-family units in rural areas, coefficients for these variables were not able to be estimated for the rural model.

5.5 Discussion and Conclusions

This study examined electric vehicle charging behavior in Utah using both trip-level and household-day-level models, with particular attention to differences between urban and rural users. The results highlight an important distinction between where chargers are available and where EV charging actually occurs.

Results from the charger-presence models (Table 5.3) show that home destinations are substantially more likely to have charging infrastructure than other destination types. This finding aligns with policymaker expectations that many (most but not all) EV users have access to charging at home. Among non-home locations, work destinations are consistently the most likely to have chargers present, while shopping, personal business, and other destinations are much less likely to offer charging. This finding also is in concordance with understanding that workplaces were some of the first non-home places to offer EV charging, as a perk for employees. As public charging at other destinations becomes more ubiquitous, this result may change. Overall, these patterns are generally consistent across urban and rural contexts, although rural destinations are more likely than urban destinations to have public EV. This finding could imply that EV users are more likely to seek out destinations with chargers when in rural areas, perhaps because places are further apart and charger density is much lower than in urban areas.

In contrast, the charging behavior models (Table 5.4) indicate that when charging occurs at the end of a trip (conditional upon a charger being present), it is actually more likely to take place at work or other non-home destinations than at home, particularly in the statewide and rural models that include home trips. However, this does not necessarily indicate that users do not primarily charge at home, only that they do not often report charging immediately after completing a trip that ends at home. This may be because they charge their vehicles later in the day (i.e., after the day’s last trip), or perhaps another household member does the charging. Home charging may still be the primary charging method for most users, as households reported charging at least one electric vehicle at the end of approximately 68% of the days included in the dataset. Instead, EV users may almost always charge after driving to work and to some other destinations with chargers. This could be related to free or discounted EV charging provided by some employers or businesses, which may be attractive when compared to cheaper but non-free home EV charging. Again, EV users in rural areas were significantly more likely to charge than in urban areas, especially for non-home trips, for potentially similar reasons as for charging presence. This further highlights the importance of public charging to support EV users who live or travel to rural areas. When considering the negative but not significant link between rural households and EV home charging at the end of the day, this suggests that public charging in particular is desirable for rural EV-owning households and for EV users traveling to and through rural areas.

Results regarding distance traveled since the last charge, layover time at the destination, and how these factors affect EV charging behavior are also informative. Across the charging models, a greater distance traveled since the last charge increases the likelihood of a charger being present for all trip types. However, it only significantly increases the odds of charging for rural trips, while distance effects are weak or nonexistent for urban trips. This indicates that rural charging behavior may be more tightly coupled to range management and necessity-driven decision-making, likely reflecting longer travel distances and fewer charging opportunities in these areas. In contrast, charging behaviors for urban users and urban trips appear to be less responsive to distance and more influenced by destination type and dwell time. Longer layover durations increase the likelihood of both having a charge and charging for urban trips (as opposed to having none or a negative relationship for rural trips), suggesting that urban charging is more opportunistic and aligned with longer stops at locations such as workplaces. Overall, rural users appear to rely more on strategic charging, while urban users rely more on opportunity charging.

Although household characteristics were mostly included in the models to control for influential but less policy-relevant factors, some results are notable. Households with multiple EVs are more likely to charge at home at the end of the day, a finding that is consistent with greater total energy demand and potentially a stronger justification for installing home EV charging infrastructure. Surprisingly, renting households are also more likely to report home charging, particularly in urban areas; the explanations for this finding are unclear. Greater access to public EV charging is weakly associated with lower odds of home charging, suggesting that there could be some substitution between public and residential EV charging.

Taken together, these results suggest that EV charging behavior reflects both necessity-driven and opportunity-driven decisions. Rural EV users appear to rely more on strategic charging tied to travel distance and charger availability, while urban EV users rely more on opportunistic charging during longer stops. From a policy perspective, the results suggest that expanding charging infrastructure at workplaces and other long-duration destinations may be particularly effective in supporting EV users. Expanding charger availability at non-home destinations may be especially important in rural areas, where charging behavior appears to be more sensitive to travel distance. Continued support for residential EV charging infrastructure is also important given the central role of home charging.

5.6 Acknowledgments

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6.0 IDENTIFYING KEY FACTORS FOR "GIG DRIVER" ELECTRIFICATION

6.1 Abstract

We determined significant factors related to having or being likely to have a battery electric vehicle (BEV) among "gig" drivers: people employed by companies offering ridehailing or delivery services (like Uber, DoorDash, etc.). Using survey data from 252 gig drivers in four major western US cities, we conducted factor analysis, estimated a structural equation model, and analyzed indirect, direct, and total effects. Key outcomes in our analysis were vehicle choice (currently have a BEV), EV beliefs (economics and personal perceptions), and future vehicle preference (likely that their next vehicle will be a BEV). The model indicated that driver age and region are associated with both using and desiring to use an electric vehicle, while income is associated mainly with current BEV usage. Additionally, our analysis highlighted the strong relationship between perceptions of the lifestyle compatibility of EVs and intended future BEV adoption. Perceptions that EVs would be personally challenging to use seemed to outweigh economic concerns around cost, range, and battery life. These findings offer several possible recommendations to promote BEV adoption among gig drivers. Programs to make EVs more affordable (like leasing options) may help lower- and medium-income drivers to overcome cost-related adoption barriers. Also, strategies should go beyond day-to-day concerns and directly address misperceptions about EVs and real concerns about how EVs might fit with people's lifestyles. This could be achieved through advertising EVs as low maintenance, user friendly, and fun, as well as opportunities to allow gig drivers the chance to try EVs on a low-risk, short-term basis.

6.2 Introduction

Widespread use of battery electric vehicles (BEVs) has the potential to improve energy and travel efficiency by reducing pollution emissions and decreasing vehicle operating costs (Du et al., 2020a; Yang & Hyland, 2024). BEV usage also supports United Nations Sustainability Development Goals 7, 11, and 13: Affordable and Clean Energy, Sustainable Cities and Communities, and Climate Action (Du et al., 2025). However, the rate of vehicle electrification varies widely—globally, within the U.S., and even within specific geographic regions and industries—complicating analysts' efforts to predict and policymaker's abilities to react to changes introduced by transportation electrification.

Among transportation markets, electrifying the "gig" driving sector—internet-enabled, app-based ride-hailing and delivery services for the transport of people and goods—has notable potential for drivers, companies, and the environment. Currently, this sector is comparatively energy-inefficient (Wenzel, 2024): It requires more energy per person per trip than public transit (due to the number of vehicles) and private driving (due to driving to reach passengers). Thus, adopting BEVs could offset this energy loss. Additionally, gig drivers drive more than most road users: upwards of 10% of miles driven in some urban areas come from ride-hailing (Fehr & Peers, 2019); and full-time "career" gig drivers drive 3-4 times more than the average American (Rajagopal & Yang, 2020; Lawrence, 2018). Accordingly, electrifying the gig sector would lower vehicle emissions by up to three times more than electrifying personal vehicles (Jenn, 2019).

Opinion within this industry may also favor electric vehicles. Gig drivers (especially career gig drivers) are more likely to consider adopting BEVs than non-gig commuters (Du et al., 2020a; Rye & Sintov, 2024; Du et al., 2020b). In fact, the city of Shenzhen, China once planned to eliminate all gas-powered or hybrid (GPH) rideshare vehicles (Du et al., 2020a). However, one study found that gig drivers are only more likely to drive hybrids, and less likely to drive full BEVs than non-gig drivers (Wenzel, 2024). Still, there is evidence that the gig sector is a desirable target for electrification.

BEV adoption also offers economic benefits for the drivers and delivery companies. Because of their low operating and maintenance costs, BEVs are sometimes more efficient (and therefore profitable) than GPHs (Yang & Hyland, 2024). Additionally, they can reduce deadheading (unproductive driving between gigs) (Loeb & Kockelman, 2019). BEV usage by gig drivers also does not increase prices for passengers; thus, it should not economically dissuade customers (Rajagopal & Yang, 2020). Additionally, full-time gig drivers may recoup some of the upfront cost of a BEV through these decreased expenses, possibly in under five years (Rajagopal & Yang, 2020). On the other hand, one study disputes these advantages, noting the potential for lost income from long charging times (Du et al., 2020b). However, algorithms for allocating requests that consider charging may limit this loss (Du et al., 2025).

Overall gig electrification has several notable advantages. Therefore, identifying factors related to gig driver electrification will support sustainable travel and commerce.

6.2.1 Background

Despite these opportunities, several obstacles inhibit large-scale gig driving electrification. Potential BEV buyers worry about public charger availability, charger speed, and vehicle cost and range (Du et al., 2020a; Krishnan & Koshy, 2021). Because of these limitations, BEVs are not consistently more profitable than GPHs for gig driving. Slow-moving traffic can exacerbate this underperformance by draining BEV batteries (Yang & Hyland, 2020).

A prominent issue is that the purchase prices for BEVs are much higher than GPHs (Ju et al., 2025). Gig drivers earn around minimum wage (Jacobs et al., 2024) and often belong to lower-income demographic groups (Ju et al., 2025). Conversely, most BEV owners have high incomes, far greater than those of most gig drivers (Rajagopal & Yang, 2020; Rye & Sintov, 2024). Unsurprisingly, many gig drivers struggle to (or cannot) afford an electric vehicle (Rajagopal & Yang, 2020). Even access to reasonable loans does not fully resolve this issue (Rajagopal & Yang, 2020).

Additionally, gig drivers often rely heavily on public chargers. High-end home chargers can be expensive and often require homeownership, making them less accessible to gig drivers (Ju et al., 2025; Rajagopal & Yang, 2020). Because of this and the amount they drive, gig drivers rely on public chargers to refuel during the day (Du et al., 2020a). Consequently, the inconsistency of current charger frequency (in the US) makes long deliveries impractical (International Energy Agency, 2023). Even in areas with sufficient chargers, their placement may not align with gig times and routes, or they may be busy when gig drivers need to charge, making them unavailable (Rajagopal & Yang, 2020). Thus, insufficient public charging severely limits gig electrification.

Although these challenges are well-documented, researchers disagree over the causes. For instance, two papers by Du et al. (2020a; 2020b) disagree on whether vehicle range discourages BEV adoption. Hathaway et al. (2021) find that women, low-income people, and minority groups are less able to afford BEVs, while She et al. (2017) and Ziefle et al. (2014) determine that women and older people are more likely to use BEVs. Additionally, Rajagopal and Yang (2020) conclude that BEV users are less likely to be women, but more likely to be older adults, while Rye and Sintov (2024) find that demographic factors are usually unassociated with BEV adoption. Lastly, Ju et al. (2025) indicate that female, White, Asian, and Hispanic gig drivers are most likely to prefer BEVs, and that BEV exposure is associated with future adoption. Other experts find that drivers who have higher incomes, work more, or drive less are more likely to consider switching to a BEV (Du et al., 2020b). In short, there is little consensus on what helps or hinders gig electrification.

One study considers the difference between attitudes and actions related to BEVs. Ju et al. (2025) find that female gig drivers are more likely to worry about charging issues and less likely to drive BEVs, but are more likely to prefer them, and that older drivers are less concerned with charging limitations. These findings imply significant differences between indicators of motivation and indicators of behavior.

Despite their many disputed associations, researchers agree that personal beliefs, such as caring about the environment, correspond to a driver's likelihood of buying a BEV. However, environmentalism seems to be less important than vehicle cost and performance, only becoming relevant when affordability is not an issue (Du et al., 2020a). When choosing a vehicle, gig drivers are usually utilitarian: switching or considering switching to BEVs because of immediate, physical concerns (Rye & Sintov, 2024). For example, charging time and public charger frequency are both major factors for choosing a BEV (Du et al., 2020a; Du et al., 2020b). This is especially true for full-time gig drivers (Ju et al., 2025). As noted earlier, vehicle choice is separate from vehicle preference, as mentally associating BEVs with positive attributes corresponds to desiring a BEV (e.g., conflating BEVs with conscientiousness) but may not actually lead to buying one (3).

These associations also seem to depend on whether gig drivers work full time. Drivers who do gig work for over 30 hours per week make up the minority of the gig driving population, but they service the most deliveries. In a recent study (Du et al., 2025), full-time gig drivers were more likely to use BEVs but also tended to have more concerns about their limitations and rely more on public chargers. They were also more likely to be male and neither very young nor very old (Du et al., 2025), which may influence their overall attitudes toward electric vehicles.

Finally, current policy recommendations for encouraging BEV adoption for gig drivers are limited and often generalized. They primarily consist of financial assistance for purchasing BEVs (Du et al., 2020a; Ju et al., 2025; Rajagoal & Yang, 2020; Sergeant, 2024), educating gig drivers (Sanguinetti et al., 2024; Sargeant, 2024; Ju et al., 2025), and increasing the number of high-quality public chargers (DeLollis & Justice, 2024; Du et al., 2020a; Rajagopal & Yang, 2024). These recommendations do not include specific amounts of aid, or clear educational mediums and messages. In fact, rebates and subsidies for low-income gig drivers are only effective for drivers who already prefer BEVs, and the minimum amount to incentivize buyers to change is higher for full-time gig drivers (Ju et al., 2025).

6.2.2 Research Objective

As our review above revealed, there are many reasons for companies and policymakers to allocate resources to electrifying the gig driving sector. Yet it is unclear *what* issues to address, and *how* to resolve them. Because of this gap in knowledge, the objective of our research was to **identify factors that directly or indirectly affect BEV choice and preference for gig drivers, across demographic categories and gig driver beliefs and characteristics**. We chose these variables either because previous research does not conclusively evaluate their relevance, or because the information seemed relevant to our questions.

To accomplish this, we created a hypothetical framework and collected survey data from gig drivers (both BEV and GPH users) in four major western US cities. Survey questions included basic demographic information, gig driving information (e.g., years doing gig work), current vehicle, current vehicle preference, and drivers' beliefs about BEVs. After collecting and cleaning the data, we analyzed this information using structural equation modeling.

6.2.3 Terminology

For the remainder of this paper, we would like to clarify a few points of vocabulary. First, a *gig driver* or *driver* refers to a rideshare or delivery driver (who uses their personal vehicle for work) employed by an app-based company such as Uber or DoorDash. This excludes truck drivers, postal workers, and other drivers who use commercial vehicles. Secondly, a *battery electric vehicle (BEV)* refers to a car fueled solely by electricity; this excludes hybrid vehicles. Correspondingly, a *gas-powered or hybrid (GPH) vehicle* refers to any non-BEV car.

Moving forward, we also define a driver's *vehicle choice* as the vehicle type (BEV or GPH) that they currently own, rent, or lease. In contrast, a driver's *vehicle preference* is about the vehicle type they imagine using for their next car; for instance, the stated likelihood that they will have a BEV for their next car.

6.3 Data and Methods

6.3.1 Data Collection

The target population for this study comprised "gig" drivers who worked for an app-based rideshare and/or delivery company—including Uber, Lyft, DoorDash, UberEats, Instacart, GrubHub, and AmazonFlex—in one of four major Western US cities: Portland, Oregon; Salt Lake City, Utah; Phoenix, Arizona; and Las Vegas, Nevada. Participants were recruited through in-person outreach (conducted by research partners at Forth Mobility) and word of mouth among the gig driving and EV communities. Key locations where gig drivers might be located (e.g., airport hold lots) and where EV drivers might spend some time (e.g., public DCFC chargers) were visited, and drivers were approached with information about the study. While all gig drivers were eligible, we were especially interested in recruiting EV gig drivers to ensure a balanced sample to compare BEV and GPH drivers. Recruitment took place from December 2021 through August 2023.

After applicants were recruited and approved (by proving they drove for a rideshare or delivery company), they filled out an online survey. This survey recorded information about drivers' app-based driving work, vehicle characteristics, perceptions of BEVs, demographic characteristics, and (for BEV drivers only) their BEV charging behaviors and experiences. In the end, 252 unique, valid, and complete responses were received (out of 268 total responses). The study procedures were reviewed and approved by Utah State University's Institutional Review

Board, protocol #12113. Full information about the data can be obtained by contacting the authors.

For the purposes of this paper, our study had two key dependent variables: vehicle choice, and vehicle preference. *Vehicle choice* (current vehicle is a BEV) was measured in response to the question: "Which kind of vehicle do you drive?" People responding "All-electric battery power only" were classified as BEV drivers, and all others (those selecting "Gas," "Hybrid," or "Plug-in Hybrid") were classified as GPH drivers. Based on the sampling protocol that sought to recruit a balance of electric and non-electric vehicle types, we obtained responses from 126 BEV and from 126 GPH drivers, as shown in Figure 6.1.

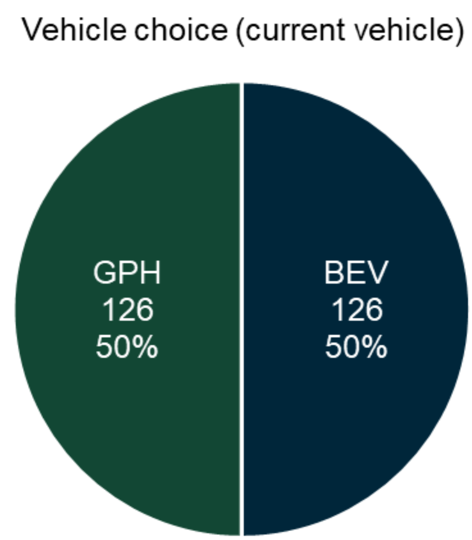

Figure 6.1: Distribution of vehicle choice responses

Vehicle preference (next vehicle will be a BEV) was measured in response to the question: "Consider your next vehicle purchase. How likely is it that your next vehicle will be a battery electric vehicle?" Respondents were given five options on a Likert-type scale: "Extremely likely," "Somewhat likely," "Neither likely nor unlikely," "Somewhat unlikely," "Extremely unlikely." Figure 6.2 shows the distribution of vehicle preference responses, overall and separately for GPH and BEV drivers. Overall, 70% of respondents were at least somewhat likely to pick a BEV for their next vehicle, but there were large differences by current vehicle choice. Just more than half (52%) of GPH drivers preferred a BEV, whereas most (87%) of BEV drivers were likely to keep using BEVs in the future. Notably, only around 5.6% of BEV drivers showed regret, reporting that it was unlikely that their next vehicle was going to be a BEV. Also, 13% of GPH drivers showed ambivalence or uncertainty, reporting that it was "neither likely nor unlikely" for their next vehicle to be a BEV.

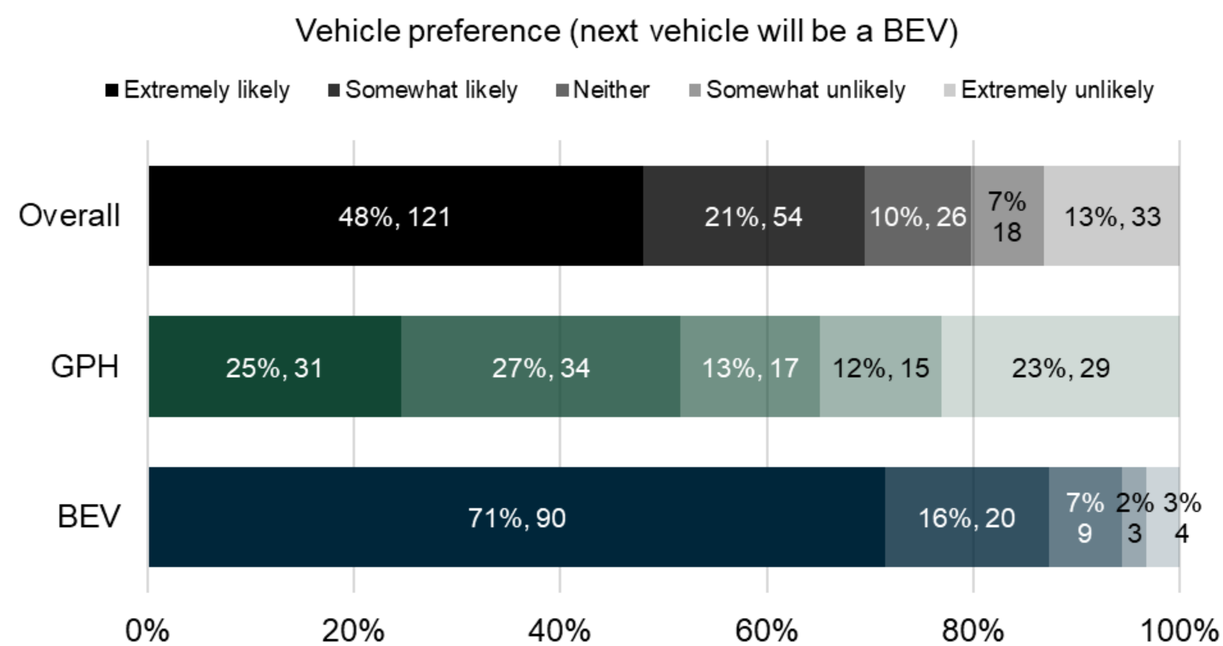

Figure 6.2: Distribution of vehicle preference responses, overall and by vehicle choice

In the process of analyzing these vehicle choice and vehicle preference outcomes, we decided to also study an intermediate set of outcomes related to EV beliefs. (See the Analysis Methods section for an explanation.) These were a series of ten questions asked in response to the following prompt: "How much do you agree with the following statements regarding all-electric (battery only) vehicles?" All questions were measured on a five-point Likert scale: "Strongly agree," "Somewhat agree," "Neither agree nor disagree," "Somewhat disagree," or "Strongly disagree." Figure 6.3 shows the distribution of responses to each of the ten EV belief questions.

Most people (more than 50%) at least somewhat agreed that EVs are too expensive, that they had concerns about battery life, and that the range of current EVs is not sufficient. These major concerns about EVs seem to be more practical: high purchase cost, uncertain battery life, and insufficient battery range. On the other hand, more than half of respondents disagreed (at least somewhat) about: not knowing how to charge an EV, an EV not fitting their lifestyle, not having confidence in the reliability of EVs, and thinking that an EV is no better than a gas-powered vehicle. So, things like self-efficacy (ability to use EVs) or the perceived benefits of EVs do not seem to be major perceptual barriers. Similarly, social or other issues related to EVs don't seem to be a major barrier, as most people disagreed that their friends or family dislike EVs, that they don't know anyone with an EV, or that they enjoy car maintenance too much to switch. These responses will be analyzed in more detail later.

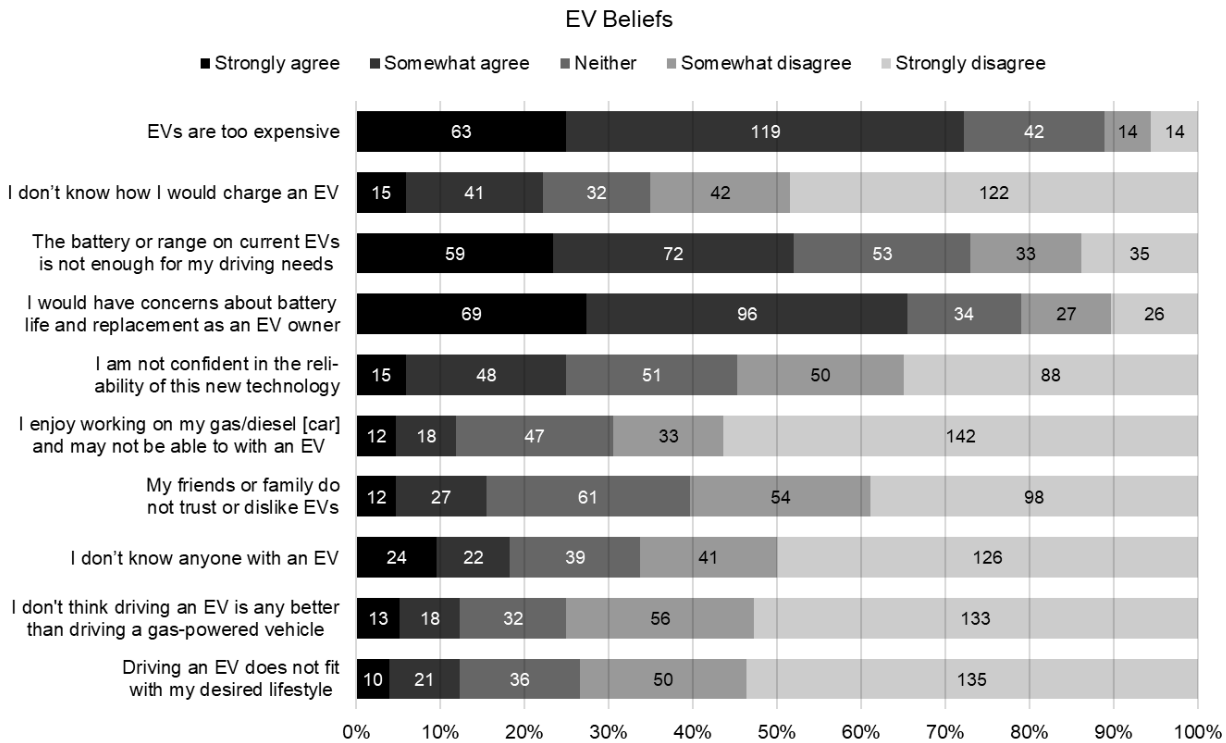

Figure 6.3: Distribution of responses about EV beliefs

To explain those outcomes, we selected a variety of independent variables from the survey, covering demographic characteristics (like age, gender, race, education, household composition, housing type, and household income), gig driving characteristics (e.g., hours and years driven, vehicle ownership, vehicle make, type of gig driving work), and a couple of questions about driver information and perceptions (sources of BEV information, perception about the adequacy of charging). While cleaning and preparing the data, we combined the initial responses into several simplified categories due to low sample sizes. We consolidated the types of app-based platforms a driver works for into delivery (e.g., Doordash, Postmates), ridehailing (e.g., Lyft, Uber), or both. We also combined responses about BEV information sources into three categories: traditional (news, advertisements, car dealerships, nonprofits, government resources, utility companies, libraries), social (social media, driver groups, word of mouth, other), and both (drivers who learn used both categories). Descriptive statistics for the independent variables are shown in Table 6.1.

Table 6.1: Descriptive statistics of the independent variables

	Categorical		Continuous	
Variable	*#*	*%*	*Mean*	*SD*
Demographics				
Age (years): 18–24	18	7.14		
25–34	77	30.56		
35–44	75	29.76		
45–64	73	28.97		
65 and older	9	3.57		
Gender: Male	174	69.05		
Non-male (female, other, or missing)	78	30.95		
Race/ethnicity: White	141	55.95		
Non-white or multiracial	97	38.49		
Undeclared or missing	14	5.56		
Education: Less than bachelor's degree	140	55.56		
Bachelor's degree or higher	112	44.44		
Number of adults in household			2.179	1.264
Number of children in household			0.861	1.589
Residence type: Single-family home	116	46.03		
Other	136	53.97		
Household income (annual): <$35,000	47	18.65		
$35,000–$74,999	107	42.46		
$75,000–$149,999	56	22.22		
≥$150,000	21	8.33		
Undeclared or missing	21	8.33		
City: Phoenix, AZ	69	27.38		
Las Vegas, NV	63	25.00		
Salt Lake City, UT	66	26.19		
Portland, OR	54	21.43		
Gig driving characteristics				
Gig driving is only income: Yes	140	55.56		
No	112	44.44		
Hours driven per week			31.844	18.260
Years of gig driving experience: 0–1	67	26.59		
1–3	74	29.37		
3–5	58	23.02		
5 or more	53	21.03		
Vehicle ownership status: Own	181	71.83		
Rent, lease, or other	71	28.17		
Vehicle make: Tesla	62	24.60		
Non-Tesla	190	75.40		
App-based platforms: Ridehailing	101	40.08		
Delivery	43	17.06		
Both	108	42.86		
Driver information and perceptions				
Sources of BEV information: Social media	73	28.97		
Traditional media	28	11.11		
Both	151	59.92		
Local charging infrastructure is adequate: Yes	84	33.33		
No	120	47.62		
Unsure	48	19.05		

6.3.2 Analysis Methods

Our hypothesized causal model is shown in Figure 6.4 (top). This framework contains three primary variables of interest: vehicle choice (current car), driver beliefs about EVs, and vehicle preference (next car). We theorized that vehicle choice affects driver beliefs, which in turn affects vehicle preference, creating an indirect effect between current choice and future preference. Additionally, we surmised that other independent factors—demographic information and gig driving characteristics—would also influence each of the three response variables.

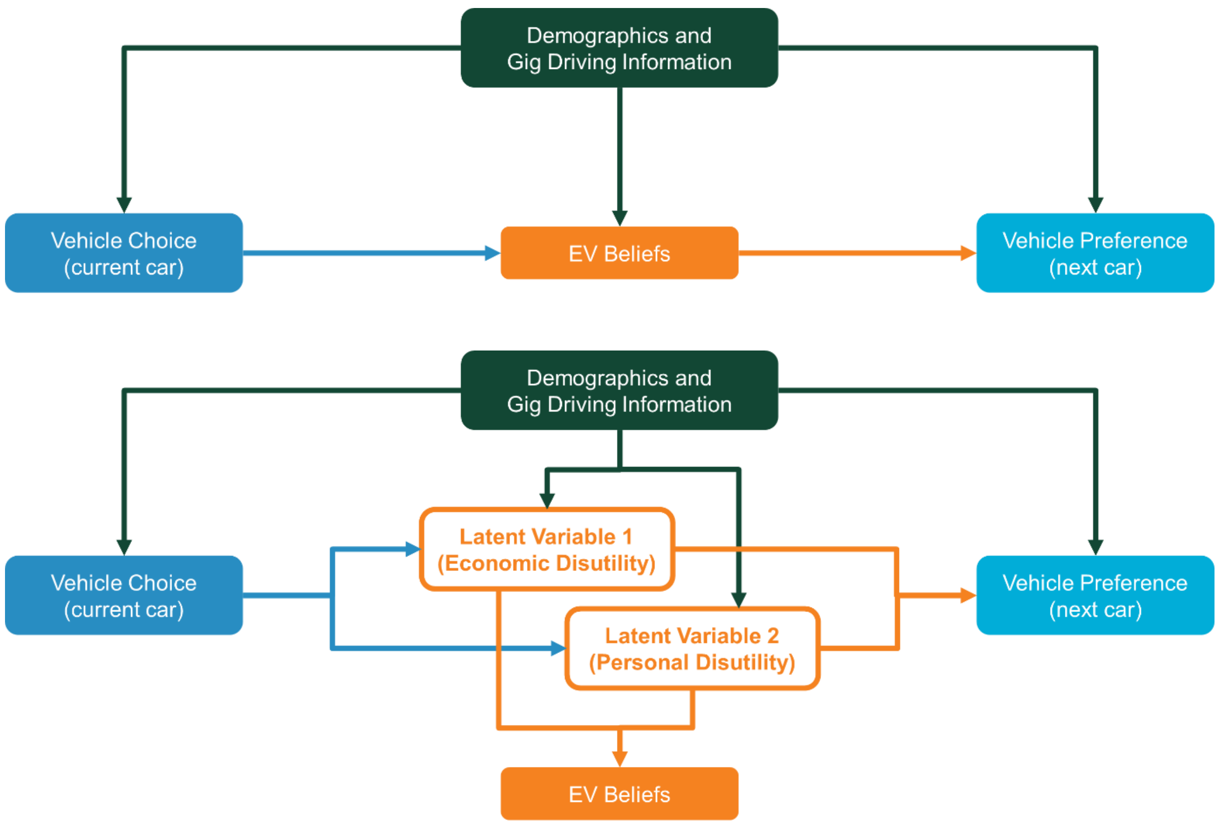

Figure 6.4: Causal model: hypothesized (top), as modeled (bottom)

This model structure is well-suited for analysis using structural equation modeling (SEM), which provides a way to simultaneously estimate many direct and indirect relationships, while considering predictors of multiple variables (BEV choice, opinion, and preference). Early attempts to use simpler approaches (e.g., t-tests, logistic regression) encountered high multicollinearity between our variables of interest. By capturing the associations between these factors using SEM, we hoped to avoid spurious correlations and focus on more useful relationships between observed variables.

Our endogenous variables were not continuous: Vehicle choice was binary (BEV or GPH), EV beliefs were ordinal, and vehicle preference was ordinal. Although SEM guidance in the presence of non-continuous outcome variables suggests using diagonally weighted least squares estimation with robust standard errors and a mean/variance-adjusted test statistic (Rosseel, 2012), we were not able to get the model to converge in this situation, likely due to the relatively small sample size (Newsom & Smith, 2020). Therefore, we settled for a second-best solution: treating the binary/ordinal variables as continuous but using an estimator that is robust to violations of normality: maximum likelihood estimation with robust standard errors and a scaled test statistic (Christoffersson, 1975). Thus, for computational ease, we converted the ordinal EV belief and vehicle preference variables to a 1–5 integer scale, where 5 was "Strongly agree" or "Extremely likely."

Furthermore, there were ten different EV belief statements. Rather than estimating influences on and of each of these separately, we used factor analysis—a structured data reduction technique—to generate unmeasured "latent variables" representing the collective variation in responses to the EV belief questions. As shown in Figure 6.4 (bottom) and detailed in the following Results section, we ultimately obtained two latent variables representing drivers' opinions about the economic utility and personal utility of EVs, the values of which explained the EV belief statement responses and predicted vehicle preference.

We ultimately estimated the SEM using the lavaan package in R (Rosseel, 2012), with the MLR estimator. Given the potentially large number of exogenous explanatory variables (see Table 6.1), we tuned our model to ensure good model fit while avoiding overfitting. This was done on an equation-by-equation basis, i.e., for a logistic regression model predicting vehicle choice, or an ordered logit regression model predicting vehicle preference. Factor scores were used for the two latent EV belief variables. For each model, we compared forward, backward, and stepwise regression to improve the formulas, using five-fold cross-validated accuracy as a measure of fitness. Next, we further improved the fit by returning to SEM for each of these four formulas and manually removing most terms with p-values 0.15 in their summary output. Finally, we estimated a single SEM containing the final set of explanatory variables predicting each outcome variable.

In a supplemental step, we performed a mediation analysis on the final SEM. This involved calculating indirect, direct, and total effects for all significant variables, to assess how they influence the final outcome, vehicle preference.

6.4 Results and Discussion

6.4.1 Factor Analysis

The first step of the analysis involved conducting a factor analysis on the ten EV belief variables in order to simplify their representation into a smaller number of concepts for subsequent SEM analysis. We conducted a two-step factor analysis: an initial exploratory factor analysis (EFA), followed by a confirmatory factor analysis (CFA). For the EFA, we started by considering one, two, or three factors, using both oblimin and geomin rotations. Based on loadings and eigenvalues, we settled on using two latent variables. In testing CFA structures, we ended up removing two items ("My friends and family do not trust or dislike EVs" and "I don't know anyone with an EV") due to low loadings (<0.4). We also removed one item because it cross-loaded on both latent variables ("I am not confident in the reliability of this new technology"), and another item because it had a low-to-medium loading and a poor conceptual fit ("I don't know how I would charge an EV"). This left us with six EV belief variables loading onto two latent variables.

The chosen CFA model is shown in Figure 6.5. The overall goodness-of-fit statistics—Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Residual (SRMR)—were all within acceptable limits (Kline, 2015). Although two of the loadings were less than desirable (<0.60), they were still acceptable (>0.40), and they showed conceptual relevance with respect to the other items. All loadings were statistically significant ($p < 0.001$). The two latent variables had acceptable internal reliability (Cronbach's alpha values of 0.62 and 0.73, respectively). Also, they were somewhat but not very highly correlated (0.61), indicating adequate discriminant validity.

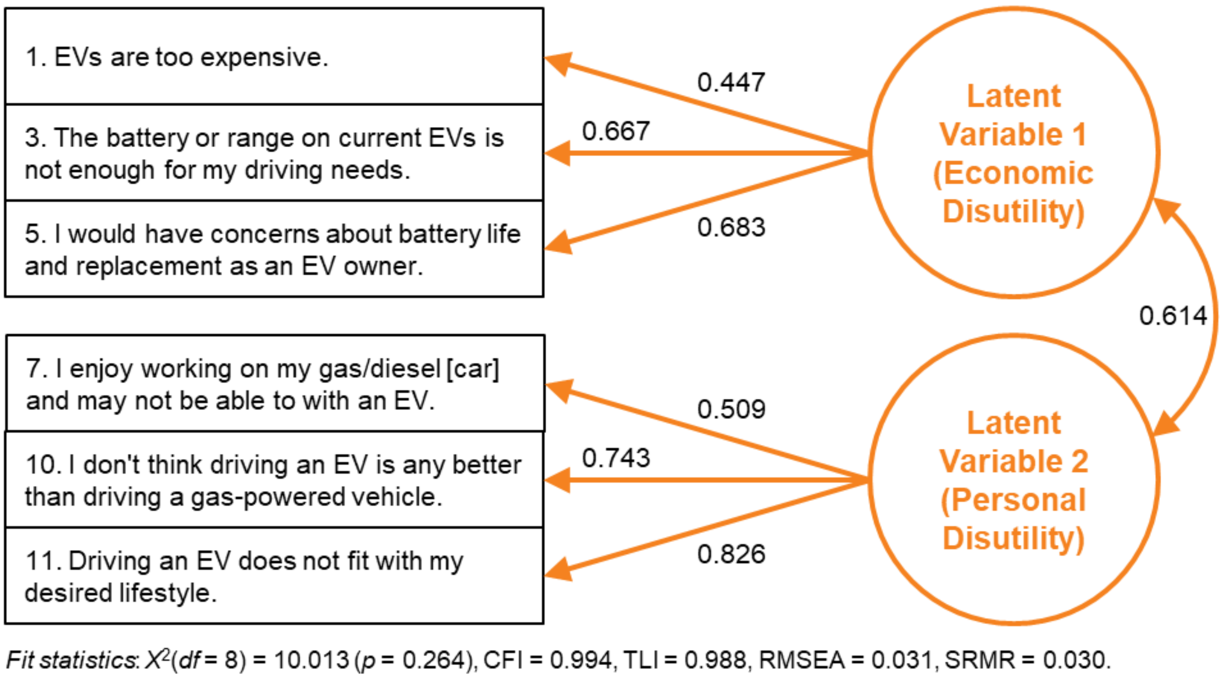

Figure 6.5: Confirmatory factor analysis results

The first latent variable combines gig driver opinions concerning the cost, range, and battery life of EVs. Thus, we interpret it to indicate the perceived *economic disutility* (EDU) of EVs: their affordability and usability for gig driving specifically. A high value for EDU means that a driver perceives EVs to be too expensive, with too much uncertainty about range and battery life. The second latent variable synthesizes opinions on whether EV drivers can do their own maintenance, whether BEVs are holistically better than GPHs, and whether EVs are compatible with a driver's lifestyle. We interpret this latent variable to indicate perceived *personal disutility* (PDU). A high value for PDU means that a driver thinks that EVs are not especially enjoyable, are no better than non-EVs, or conflict with a driver's standard routines.

6.4.2 Structural Equation Model

The final estimated SEM results are shown in Table 6.2. Results are grouped (and discussed below) by the outcome variable being considered: vehicle choice (current vehicle is a BEV), EV beliefs (economic disutility of EVs, personal disutility of EVs), and vehicle preference (next vehicle will be a BEV).

Table 6.2: Structural equation model results

Variable	*Est.*	*SE*	*z*	*p*
Vehicle choice (current vehicle is a BEV)				
Age (years): 65 and older	-0.287	0.145	-1.986	0.047
Household income (annual): <\$35,000	-0.170	0.076	-2.236	0.025
≥\$150,000	0.218	0.096	2.261	0.024
City: Las Vegas, NV	-0.138	0.075	-1.848	0.065
Salt Lake City, UT	-0.185	0.074	-2.487	0.013
Portland, OR	0.183	0.083	2.191	0.028
Vehicle ownership status: Rent, lease, or other	0.298	0.061	4.884	<0.001
App-based platforms: Ridehailing	0.106	0.057	1.841	0.066
Gig driving is only income: No	0.212	0.057	3.706	<0.001
Years of gig driving experience: 0–1	0.208	0.063	3.294	0.001
EV beliefs: Economic disutility of EVs				
Vehicle choice (current vehicle is BEV): True	-0.316	0.191	-1.653	0.098
Age (years): 35–44	-0.317	0.162	-1.964	0.050
45–64	-0.454	0.193	-2.357	0.018
Household income (annual): ≥\$150,000	-0.578	0.353	-1.638	0.101
App-based platforms: Delivery	-0.523	0.209	-2.504	0.012
EV beliefs: Personal disutility of EVs				
Vehicle choice (current vehicle is BEV): True	-0.699	0.190	-3.687	<0.001
City: Portland, OR	-0.354	0.123	-2.880	0.004
Vehicle preference (next vehicle will be a BEV)				
EV beliefs: Economic disutility of EVs	0.255	0.311	0.819	0.413
Personal disutility of EVs	-1.063	0.254	-4.179	<0.001
Age (years): 65 and older	-0.606	0.295	-2.053	0.040
City: Salt Lake City, UT	-0.583	0.173	-3.376	0.001
Gig driving is only income: No	0.403	0.135	2.978	0.003
R^2 values: 0.248 for vehicle choice, 0.116 for economic disutility, 0.136 for personal disutility, 0.574 for vehicle preference.				

6.4.2.1 Vehicle Choice

The results for the variables associated with BEV choice reveal that drivers of retirement-age (over 64 years old) and those in the lowest income bracket were less likely to drive BEVs. In contrast, the highest-income gig drivers, those with less than a year of experience, drivers who rent or lease their vehicles (instead of owning them), people with income outside of gig driving, and those who only drive for ridehailing platforms (not delivery) were more likely to have BEVs.

Location also seemed to influence this decision: Portland-based drivers were more likely to choose BEVs than Phoenix drivers, while drivers in Salt Lake and Las Vegas were less likely to drive them.

The findings around income are consistent with the assumption that EVs appeal more to higher-income households due to their higher upfront costs. The ownership status finding is interesting: Perhaps flexible vehicle leasing programs (including some from gig driving companies) can help to lower the barrier to entry and mitigate concerns over making a commitment to a technology (BEVs) that has perceived risks involved. New drivers also seem to be more likely to be going electric, which could also reflect an electric bias against incumbent participants in this labor pool; although it could also be related to the many newer EVs that came on the market during the study period. The slight preference for EVs among ridehailing-only drivers might reflect a perceived premium that EVs can offer passengers, such as a smoother ride or a point of conversation that might lead to tips and positive ratings and reviews.

6.4.2.2 EV Beliefs

Several factors—age, household income, app-based platform type, region, and vehicle choice—directly influenced perceived economic disutility of EVs. Recall, people with higher perceived economic disutility are more concerned about the cost, range, and battery life of EVs. Middle-aged drivers (age 35–64), those with the highest household incomes (≥$150,000) (on the edge of marginally and not significant), and drivers who only work for delivery platforms were less likely to worry about these economic aspects of EVs. In addition, current BEV drivers perceived less economic disutility of EVs.

Few factors were significantly associated with perceived personal disutility of EVs, relating to lifestyle, enjoyment, and normative judgments about EVs vs. GPHs. Drivers working in Portland were less likely to have these personal disutility concerns, as did current BEV drivers.

It makes sense that current BEV drivers might have fewer concerns or negative beliefs about EVs, especially perceived personal disutility. EVs may have been more suitable for these drivers, reflecting a self-selection based on differences in perceived usefulness of different vehicle types for gig driving. Another explanation is that experience using EVs can help to overcome negative perceptions about how hard or expensive it might be to use EVs for gig driving work.

The income finding also has a logical explanation: Drivers from higher-income households may be more resilient to uncertainty in EV costs, up-front and in the long run. Middle-aged drivers may also be more stable in their economic situation than younger or older drivers. We are unsure why delivery-only drivers expressed less concern about the economic utility of EVs.

The factors influencing these related but distinguishable sets of EV beliefs are also a notable finding. Few demographic characteristics were useful in predicting perceived personal disutility of EVs, meaning that either such perceptions may be idiosyncratic, or that there are other things that we did not capture in our study's survey that could be useful in explaining these variations in EV beliefs among gig drivers.

6.4.2.3 Vehicle Preference

Among the factors associated with vehicle preference (the stated likelihood that a driver's next vehicle will be a BEV) were age, city, gig driving characteristics, and EV beliefs. As age increased, gig drivers were less likely to prefer a BEV, with people of retirement age being least likely. Drivers working in Salt Lake City were also the least likely of any city to prefer BEVs. People for whom gig driving was not their only source of income were more likely to prefer BEVs for their next vehicle. Notably, people with higher perceived personal disutility of EVs had much lower preferences for BEVs. On the other hand, perceived economic disutility did not have a significant effect on vehicle preference, and the coefficient was actually positive, not negative.

Similar to our results for vehicle choice, age seems to be an important demographic factor influencing BEV preferences, with older drivers being more skeptical. This aligns with other research in which older adults are less likely to adopt EVs (Rajagopal & Yang, 2020), after accounting for income effects. People with incomes outside of gig driving may depend less on the gig economy to help them cover the higher upfront costs of EVs.

The difference in effects for EV beliefs is interesting and offers notable insights. It appears that personal perceptions about EVs are the major barrier to preference, at least more so than economic perceptions. Perhaps people can more easily overcome their own concerns about practical factors (like cost and reliability) when thinking about their future vehicle preferences, whereas personal barriers related to lifestyle and other factors are more difficult to overcome. Maybe people with economic concerns can imagine that costs may come down and battery range/life may increase in the near future, but other people have a hard time imagining themselves using a BEV. This suggests that, while reducing costs and improving the reliability and longevity of EVs is important, it is also essential to provide opportunities for skeptics to experience using EVs in their gig driving and in their life. In short, focusing on "hearts and minds" is just as important, if not more so, than focusing on wallets and pocketbook issues around EVs.

6.4.2.4 Mediation Analysis

Following the estimation of the SEM, we analyzed mediation by calculating indirect, direct, and total effects for all significant variables, assessing their cumulative impact on the vehicle preference outcome. Results of this analysis are shown in Table 6.3.

Age remains a strong and significant factor, with older adults (those 65 and older) being especially less likely to prefer a BEV for their next vehicle. The indirect effects of income acting through the EV beliefs variables were not statistically significant. Portland gig drivers were significantly more likely to prefer BEVs, but only indirectly through being more likely to currently have a BEV and less likely to perceive personal disutility. On the other hand, gig drivers in Salt Lake City were the least likely to both own and want to own a BEV for this kind of work. Only the direct effect of people whose sole income was gig driving was significant. Gig driving characteristics such as years of experience and vehicle ownership had significant indirect effects on vehicle preference, through vehicle choice and EV beliefs. On the other hand, what kind of app-based platforms people drove for did not seem to make a difference on BEV preferences, with non-significant indirect effects.

Table 6.3: Indirect, direct, and total effects for all significant variables

	Effect on vehicle preference (next vehicle will be a BEV)					
Variable	*Indirect*	*p*	*Direct*	*p*	*Total*	*p*
Endogenous variables						
Vehicle choice (current vehicle is BEV)	0.663	0.009	0.000	--	0.663	0.009
EV beliefs: Economic disutility of EVs	0.000	--	0.255	0.413	0.255	0.413
Personal disutility of EVs	0.000	--	-1.063	0.000	-1.063	0.000
Demographics						
Age (years): 35-44	-0.081	0.453	0.000	--	-0.081	0.453
45-64	-0.116	0.488	0.000	--	-0.116	0.488
65 and older	-0.190	0.104	-0.606	0.040	-0.797	0.011
Household income (annual): <$35,000	0.053	0.139	0.000	--	0.053	0.139
≥$150,000	-0.003	0.980	0.000	--	-0.003	0.980
City: Las Vegas, NV	-0.091	0.131	0.000	--	-0.091	0.131
Salt Lake City, UT	-0.122	0.066	-0.583	0.001	-0.706	0.000
Portland, OR	0.498	0.006	0.000	--	0.498	0.006
Gig driving characteristics						
Gig driving is only income: No	-0.055	0.431	0.403	0.003	0.349	0.028
Years of gig driving experience: 0–1	0.138	0.042	0.000	--	0.138	0.042
Vehicle ownership status: Rent, lease, or other	0.197	0.016	0.000	--	0.197	0.016
App-based platforms: Ridehailing	0.070	0.141	0.000	--	0.070	0.141
Delivery	-0.133	0.426	0.000	--	-0.133	0.426

6.5 Conclusion

In this study, we sought to identify factors associated with adopting or considering adopting fully battery-electric vehicles (BEVs), specifically among the gig driving community, (those who work for companies providing ridehailing or delivery services). To that end, we surveyed 252 gig drivers in four major western US cities and analyzed their responses to find key indicators of BEV choices, opinions, and preferences. In this section, we discuss the implications of our study's key findings, and we mention some study limitations and opportunities for future work.

6.5.1 Implications

One useful finding is that driver affluence (measured as annual household income) directly affects BEV choice and perceived economic disutility, but not BEV preference or perceived personal disutility. This implies that many gig drivers interested in EVs may be hesitant due to higher upfront costs, whereas wealthier drivers have the financial security to risk investing in an EV. Similarly, people who had other non-gig sources of income were also more likely to have a BEV or choose one in the future. Thus, strategies to reduce the purchase price of EVs, especially for gig drivers with limited incomes, may be effective at encouraging BEV adoption within the gig driving market. The positive association between BEV choice and not owning one's vehicle suggests that leasing programs for gig drivers may be an effective way to encourage people to try an EV for this kind of work without the risks of fully committing.

This policy implication is supported by the fact that nearly all current BEV gig drivers would be somewhat or extremely likely to pick a BEV for their next vehicle. Gig drivers who currently own BEVs were more likely to have positive perceptions and less likely to view EVs as having economic or personal disutilities. It follows that getting gig drivers to try BEVs on a temporary basis may be an effective electrification strategy, especially for overcoming personal perception barriers.

Our analysis also indicated that driver age and location influence both perception and adoption of BEVs. Both factors have physical and cultural implications. Age often indicates physical ability, and different generations have markedly different sociocultural viewpoints. Similarly, the cities surveyed have unique political and cultural leanings, are in very different geographic climates, and have varying levels of BEV-friendly infrastructure. We cannot ascertain which (if any) of these features are the reason for these associations. But our analysis clearly indicates that characteristics of Portland, Oregon are friendlier to BEVs than Salt Lake City, Utah. This could be due to differences in the number and location of (especially fast) public EV charging stations, differences in the populations who do gig driving work, or a combination of factors. Older drivers are much less likely to use and prefer BEVs, whereas newer gig workers are more likely to drive electric. If generational cohort effects outweigh differences due to lifecycle stages, then we might naturally assume higher EV adoption as younger generations make up a larger share of gig drivers. Also, efforts to promote BEV electrification should take the difference between these ages and locations into consideration. For instance, advertising efforts should consider how different regional and generational audiences will react to various targeted messages.

Besides these interesting associations, it is also important to point out the many variables that ultimately had no significant association with any of our four EV-related outcomes.

Regarding demographics, gender, race/ethnicity, and educational attainment seemed to play no major role in EV choice, preference, or beliefs. Similarly insignificant were household composition and housing characteristics like the number of adults or children and the type of residence. Several gig driving characteristics and driving information were also not relevant in any submodel of the SEM, most notably hours driven per week (as a measure of intensity of gig driving work) and sources of information about BEVs. It could be that other aspects of peoples' lives and circumstances are more influential.

Finally, the SEM model illustrates the effect of EV-related perceptions and beliefs on future BEV preferences. Believing that BEVs are incompatible with one's lifestyle is negatively associated with BEV preference – in fact, this relationship has the largest coefficient in our model. Conversely, believing that BEVs are not affordable or usable for gig work has a very weak, even potentially positive effect on vehicle preference. This indicates that personal utility is far more integral to a gig driver's willingness to adopt a BEV than economic utility. Thus, efforts to overcome these perceived disutility aspects and personal barriers may be more effective in the long run than economic interventions.

As a result, these findings illustrate the beliefs and biases that most limit gig driving electrification: those concerning lifestyle compatibility. One possible approach to overcoming this stigma could be marketing BEVs as low-maintenance vehicles that are easy to use and refuel without assistance. Where biases are well founded, future BEV designs should incorporate features that allow drivers to self-maintain their vehicles and seamlessly transition from using GPHs to driving BEVs. Increasing the amount of available public charging could also assure gig drivers that BEVs are compatible with their work. Finally, some gig drivers just might not imagine using EVs due to other personal or social reasons. Perhaps marketing materials that highlight the fun or exciting aspects of EVs might be more effective for these populations.

Overall, these data indicate income and age as key demographic factors for electric vehicle choice, and personal EV belief as one of the primary motivators of electric vehicle preference, among gig drivers in the western US. We also found several opportunities for policy change in regard to vehicle affordability and marketing. Although our models indicate that the variables we examined do not capture the entire story of how gig drivers develop vehicle preferences and choose their vehicles, this research offers a foundation for future policy and study. Some underexplored topics in this area include the adoption of hybrid vehicles vs. BEVs, surveying BEV gig drivers who plan to switch back to GPHs, and identifying additional variables related to BEV adoption and preference.

6.5.2 Limitations

A key limitation of our study is the relatively small sample size (252 gig drivers). To preserve many variables with low frequencies, we combined many categories. A larger sample size would likely be able to provide more nuanced and detailed results; although, it was already very difficult to recruit this sample. For instance, very few demographic or gig driving characteristics were found to significantly explain perceived personal disutility of EVs, beyond current vehicle choice and city. Given the outsized importance of this factor on future BEV preferences, it would be useful to explain a larger share of the variation in these responses using other variables. For instance, environmental values or political orientation might play a key role in shaping personal perceptions of EVs and how well they might fit into someone's lifestyle.

Additionally, there is potential for response bias (respondents knew they were being surveyed about electric vehicles) and sampling bias (the recruitment procedures included some snowball sampling). Thus, while our results indicate relevant issues and factors, they are not exhaustive or perfect. Further study is necessary to verify our results more rigorously, including continued surveying of a larger number of gig drivers. This is especially important as gig economy working conditions evolve and a greater number of BEV models enter the market.

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7.0 CONCLUSIONS

7.1 Summary

This research project achieved a greater understanding of the factors affecting EV adoption, use, and charging behaviors in Utah, including differences between urban and rural areas. It utilized three different key datasets: Utah's 2023 household travel survey, 2015–2024 Utah vehicle registrations by county, and a 2021–2023 survey of "gig" drivers about EVs. Through a variety of statistical analyses of these data, the research team identified factors associated with key outcomes (vehicle ownership, EV adoption, travel behaviors, charging behaviors, and EV perceptions and preferences), and any differences between more urban and more rural areas (within vs. outside of the Wasatch Front) of Utah. This chapter summarizes key findings, discusses limitations, presents recommendations, and describes an implementation plan.

7.2 Findings

Chapter 2.0 analyzed up to ten years (2015–2024) of trends in EV registrations in Utah (by county and vehicle class) and developed and interpreted logistic models to estimate future adoption rates. Currently (as of 2024), EVs of all types—battery-electric, plug-in hybrid, and standard hybrid EVs—make up a larger share of passenger cars (5.6%) than light trucks (3.8%). If current trends continue, by 2050 (26 years from 2024) around half of all registered vehicles in Utah will be EVs. Light trucks are experiencing a more rapid electrification; current trends suggest that it will take just 14 years (from 2024) to reach 50% electric light trucks in Utah. Although urban areas have higher rates of EV adoption, rural areas of Utah are experiencing rapid EV growth, especially for BEVs and light trucks.

Chapter 3.0 analyzed 2023 Utah household travel survey data using a series of regression models of household vehicle ownership and EV adoption, explained by household characteristics, proximity to public charging, and location (urban vs. rural). Results were largely similar regardless of whether EV adoption was defined as having a BEV or either a BEV or PHEV. Household income (especially those with incomes of $100,000 or more) was a consistent and significant predictor across all models (and regions), playing a central role in both vehicle ownership and EV adoption. Education and housing tenure also predicted EV adoption: College-educated households and homeowners were more likely to have EVs. The number of household vehicles was positively associated with EV adoption in urban areas but not rural areas, suggesting EVs are often secondary vehicles for urban households. Accessibility to public EV charging infrastructure had a modest but positive association overall, suggesting that improved charging infrastructure could impact vehicle electrification, if expanded. Overall, the factors influencing EV adoption remained largely the same across urban/rural contexts, suggesting that there may be similar motivations for having an EV for urban and rural households, at least among early adopters.

Chapter 4.0 also analyzed 2023 Utah household travel survey data using a series of regression models of household- and vehicle-day travel outcomes, including no travel, trip frequency, distance, and duration. The models compared EVs (vs. non-EVs) and EV-owning households (vs. non-EV owning households), and the travel behavior outcomes were explained by socio-demographic, household, and geographic factors (including differences in urban vs. rural settings). Results indicated that household structure (workers, students, children) and income strongly shaped travel participation and intensity, while older age groups were consistently associated with reduced household travel. Vehicle availability was a robust predictor of trip frequency, distance, and duration. Although EV-owning households did not exhibit statistically significant differences in travel outcomes compared to non-EV households, EVs themselves were less likely to not be used on a given day, and they made more daily trips, at least in urban areas. This remained the case whether EV was defined as a BEV or either a BEV or PHEV. Additionally, regional contrasts were evident: Rural households showed stronger income effects, with higher-income rural households traveling substantially more than their lower-income counterparts, whereas urban households exhibited smaller income-related differences in travel. Overall, the findings suggest that EV ownership itself does not substantially alter daily travel patterns once household and demographic characteristics are considered, but spatial context amplifies socioeconomic differences in mobility.

Chapter 5.0 used EV-only data (for BEVs and PHEVs) from the 2023 Utah household travel survey to analyze three charging behavior outcomes: the presence of a charger at a trip's destination, choosing to charge at the end of a trip, and household choosing to charge at home at the end of the day. Regression models predicted these trip-level and household/day-level outcomes, explained by household, driving, and locational (urban vs. rural) factors. Results showed that charger availability was strongly associated with destination type, with home and work destinations having the highest odds of charger presence. Rural destinations had moderately higher odds of charger availability than urban destinations. When a charger was present, charging was most likely at work destinations, and rural users were more likely than urban users to charge at trip destinations. Distance traveled since the previous charge was associated with charger presence and with charging behavior for rural trips but not for urban trips. Layover duration was positively associated with charging in urban areas but not or negatively associated with charging in rural areas. Household models indicated that multi-EV households and renting households were more likely to charge at home, and that greater access to public EV charging slightly decreased the odds of charging at home. Overall, the results suggest that EV charging behavior reflects both necessity-driven and opportunity-driven decisions, with rural users relying more on distance-based strategic destination charging and urban users relying more on opportunistic charging.

Chapter 6.0 used survey data (2021–2023) from “gig” drivers in four western US cities (including Salt Lake City) and analyzed current use of BEV or not, EV-related economic and personal beliefs, and future vehicle preference for a BEV, explained by demographics and gig driving information. The structural equation model indicated that driver age and region were associated with both using and desiring to use an electric vehicle, while income was associated mainly with current BEV usage. Additionally, the analysis highlighted a strong relationship between perceptions of the lifestyle compatibility of EVs and intended future BEV adoption. Perceptions that EVs would be personally challenging to use seemed to outweigh economic concerns around cost, range, and battery life.

7.3 Limitations and Challenges

The models of Utah EV registration data in Chapter 2.0 assume that EV adoption follows an S-shaped technology adoption curve, and that past trends predict future levels of adoption. In reality, market trends in EV ownership may be highly dependent on economic and policy factors, including the price and supply of new and used EVs (including for specific vehicle classes), any government subsidies or manufacturer discounts (including tax credits and rebates), the price of gasoline and electricity, registration fees and road usage charges, and many other considerations. These specifics were not able to be accounted for in the forecasts of EV registrations in Utah.

The models of EV adoption, travel behavior, and charging behavior in Chapters 3.0, 4.0, and 5.0 used as much structured information from the 2023 Utah household travel survey as possible. However, there were several potential explanatory factors (as hypothesized from the literature) that were unable to be included because they were missing from the dataset. Notable examples included: information about at-home charging availability or feasibility; destination charging availability, quality, and price; and social/psychological factors like attitudes toward EVs, technology, and the environment. Additionally, the HTS was conducted in 2023; the continued growth in EV adoption and charging stations in Utah, as well as new EV models on the market, might be slowly changing the factors that explain who owns an EV and how EVs are being used and charged.

The model of gig driver EV choice, beliefs, and preferences in Chapter 6.0 were limited by the relatively small sample size of the survey: 252 gig drivers. A larger sample size in a future study would likely be able to provide more nuanced and detailed results. It would also be useful to collect more information (e.g., about environmental values or political orientation) to help better explain perceived disutility of EVs, given the importance of this factor on future BEV preferences. Also, the data and analysis may have been susceptible to response bias and sampling bias. Finally, the survey was conducted mostly in 2022 and 2023; more up-to-date data could shed light on recent trends in the electrification of the gig driving industry.

7.4 Recommendations and Implementation Plan

The implications of the key findings of this research project (summarized in the previous section) offer several recommendations and suggestions for actions that UDOT and others may implement.

First, the analysis of EV registration data yielded useful insights about trends and forecasts. As new EV registration data is released, the State of Utah should continue to monitor trends and update forecasts, potentially using an online dashboard such as the one created for this research project (see Figure 2.2). This dashboard could be implemented by either Utah State Tax Commission (who publishes the data) or UDOT (who may be more invested in the outcomes), or a third party could be hired to develop and maintain the EV registration data dashboard. This is anticipated to be a low-cost effort.

Second, the analysis of Utah household travel survey data indicated that even though EV adoption was more likely among higher-income, higher-educated, and homeowning households, there were relatively few differences in the factors influencing the aggregate daily travel behaviors of EV-owning and non-EV-owning households. This suggests that our current understanding of the influences on travel behaviors (including those that are embedded into regional and statewide travel demand models) likely largely holds for an EV future, at least when considering early EV adopters. This recommendation is more of a null finding: that existing travel models may not require significant modification now to accommodate forecasts of travel demand in a future with higher EV penetration rates. No implementation is needed.

Third, nevertheless, looking more finely at EV (vs. non-EV) travel behaviors and trip-level EV-only charging behaviors, there were some notable differences that point toward urban and rural distinctions. For travel behaviors, EVs themselves were less likely to not be used on a given day than non-electric vehicles, and EVs made more daily trips than non-EVs, at least in urban areas. For charging behaviors, rural EV trips were more likely to end at a destination with a charger and were more likely to result in a charging event. Overall, these results suggest that rural EV users (residents and visitors) are more strategic about their use and charging of EVs, whereas urban EV users can be more opportunistic. This behavior is largely out of necessity: public charging stations are fewer and farther apart, and rural travel distances can be longer. To provide acceptable levels of service in support of the rapid growth in EV ownership in rural areas (as well as the increasing use of EVs by non-residents in tourist areas and along major travel corridors), it is recommended that UDOT focus attention on planning and monitoring the demand for public EV charging, more so in rural areas of the state than in urban areas. Rural EV charging stations could see more peaked demand patterns that require monitoring and management. Perhaps a study could identify ways to track the utilization of rural public EV charging stations, assess performance over time, and inform future charging infrastructure investments.

Fourth, the gig driving economy is a sector that has great opportunities for electrification but based on the analysis of drivers in four cities, Salt Lake City had the lowest levels of both current BEV use and likely future BEV adoption. This finding recommends various strategies to increase the uptake of electrification of the gig driving sector, especially in Utah. One approach could seek to lower the costs of committing to an EV for gig driving work; strategies include providing vehicle leasing options through ridehailing or delivery companies, or through rental car agencies or traditional dealerships. This would also allow gig drivers to try going electric without fully committing. Another set of strategies would focus on advertisements and other marketing efforts to portray EVs as low maintenance, user friendly, and fun. Messages should be targeted to account for regional and generational differences in audiences. This work could be implemented by private companies or public agencies hiring advertising firms. Finally, ensuring that there is ample available public EV charging (especially DCFC ports) in places that are convenient for gig drivers (e.g., airport hold lots, hotels, commercial and residential areas) would make it easier for gig drivers to incorporate EVs into their work and their lives. UDOT could help coordinate between ridehailing/delivery companies and major landowners to facilitate the construction of public EV charging in proximity to such places.

Fifth, despite using the latest data available at the time, this study’s datasets are already one-to-three years old. Chapter 2.0 used EV registration data through the end of 2024; Chapters 3.0, 4.0, and 5.0 used household travel survey data from 2023; and Chapter 6.0 used gig driver surveys conducted from late 2021 through mid-2023. The analytical insights obtained from these data (e.g., factors associated with EV adoption, use, and behavior) are still relevant in 2026. Nevertheless, the background conditions may have changed as the transportation electrification ecosystem in the US continues to evolve: newer EV models enter the market with different ranges and performances; EV-related policies such as tax credits and vehicle registration/use fees change; and new and upgraded EV charging stations are installed. UDOT staff or partners should continue to monitor trends in transportation electrification (EV adoption, vehicle performances, charging networks) to monitor for large-scale changes. To obtain more up-to-date sentiment about EVs and transportation electrification, UDOT could consider deploying or contracting an ongoing or periodic statewide survey about EV-related attitudes, adoption, use, and behavior.