Investigating Heterogeneity in Private Vehicle Ownership, Preferences towards Alternative Fuel Vehicles, and Adoption of Shared Mobility Options

By

XIATIAN IOGANSEN

DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Transportation Technology and Policy

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA

DAVIS

Approved:

____

Giovanni Circella, Chair

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David S. Bunch

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Alan Jenn

Committee in Charge

2024

Abstract

In recent decades, emerging technologies have significantly transformed the transportation sector, offering a wider range of vehicle options and mobility alternatives. However, the recent COVID-19 pandemic disrupted many aspects of daily life, likely leaving long-lasting effects that further complicate our understanding and prediction of individuals' activity-travel patterns, vehicle ownership decisions, and fuel type preferences. Despite efforts by the State of California and the rest of the U.S. to promote sustainable travel, more behavioral shifts are needed to reduce car dependence, encourage multimodal transportation, and accelerate the electrification of both privately owned and shared vehicle fleets. Further research is needed to identify the factors that motivate or hinder these shifts, and to understand their heterogeneous impacts across subpopulations, which vary based on personal attitudes, socio-demographic characteristics, geographic contexts, and COVID-related factors. This dissertation aims to address these research gaps through four interconnected studies.

The first two studies examine the determinants of vehicle ownership and fuel type choice by consumers for privately owned vehicles. In the first study (Chapter 2), I construct an integrated choice and latent variable (ICLV) model to jointly model current vehicle fuel type choices and future interest in alternative fuel vehicles (AFVs) among 3,260 Californian residents. The findings highlight the critical role of latent attitudes (including those related to environmental concerns, tech-savviness, car utilitarianism, and residential location preferences) and socio-demographic factors in shaping individuals' vehicle fuel type choices. Exposure to battery electric vehicles (BEVs) in residential locations and workplaces increases the likelihood of AFV adoption. Individuals' current user experience with AFVs has a positive effect on their interest in these vehicles. Based on consumer intentions reported in 2018, I estimate that the potential natural ceiling for AFV adoption in California could reach 41% of the adult population.

In Chapter 3, I extend my study to examine the impacts of the COVID-19 pandemic on household vehicle ownership. Using an ICLV model and a longitudinal dataset of 1,612 US residents, I analyze

changes in their household vehicle counts during the pandemic (spring 2020 to fall 2023) and expected changes after the pandemic (fall 2023 to fall 2026). The results indicate that novelty-seeking individuals are more engaged in vehicle transactions, such as adding, removing, or replacing vehicles. Younger adults, households with children, and families experiencing an increase in the number of adults or children are more likely to acquire additional vehicles to meet evolving travel needs. Entering the workforce and rising household income during the study period also contribute to vehicle acquisitions. Moreover, a higher frequency of commuting reduced the likelihood of shedding vehicles in the past and continues to increase the likelihood of vehicle purchases in the future. Finally, households that shed vehicles during the pandemic often expect to reacquire them afterward, counteracting the vehicle reductions achieved during the pandemic.

Ridehailing services have the potential to serve as a practical alternative to private vehicles and help reduce environmental impacts when powered by clean-fuel vehicles and integrated with other less-polluting modes like public transit and micromobility. Accordingly, the rest of my dissertation focuses on ridehailing riders (in Chapter 4) and ridehailing drivers (in Chapter 5). In Chapter 4, I estimate a weighted latent class cluster analysis among 5,053 California residents and identify four distinctive traveler groups. *Drive-alone Users* (53%) and *Carpoolers* (28%) are predominantly car-oriented and less multimodal, whereas *Transit Users* (15%) and *Cyclists* (4%) exhibit greater multimodality. *Transit Users* account for the highest rate of ridehailing adoption and usage and are also more prone to using pooled ridehailing services. If ridehailing were not available, users would generally replace ridehailing with the modes they use most frequently. For instance, car-oriented travelers are more likely to substitute ridehailing with car trips, whereas non-car-based travelers are more inclined to replace ridehailing with less-polluting modes.

Finally, Chapter 5 examines the vehicle fuel type choices of ridehailing drivers. Using data from 1,099 California ridehailing drivers, I estimate an ICLV model to explore their motivations and barriers to AFV adoption. The findings reveal that older drivers, those solely working for ridehailing, and residents in multi-family dwellings are more likely to obtain vehicles with the intention of using them for ridehailing work. Additionally, latent factors such as positive *attitudes* towards EVs and favorable *subjective norms* around EVs are positively correlated with BEV adoption, while *perceived barriers* to EVs hinder their adoption. Access to charging infrastructure also positively impacts BEV adoption. Home chargers have a stronger impact among drivers who obtained their vehicles without the intention of using them for ridehailing, while public chargers are more important for those who acquire vehicles with the intention of using them for ridehailing work. Federal incentives have a more substantial impact on EV adoption compared to state and local incentives, although their effectiveness depends on the driver's familiarity with the programs. The impact of federal incentives is especially pronounced among drivers who acquired vehicles with the intention of using them for ridehailing work, with the potential to increase the BEV market share by 10 percentage points if all drivers were highly familiar with these incentives.

Acknowledgements

I have been incredibly fortunate to be surrounded by exceptional mentors, colleagues, family, and friends throughout the journey of completing this dissertation. I would like to express my deepest gratitude to everyone who has supported me along the way.

I owe my heartfelt thanks to my advisor, Professor Giovanni Circella, whose guidance and support were instrumental in shaping this dissertation. You have been an extraordinary mentor, encouraging me to always set high standards on my research and to maintain a keen attention to detail. Your generosity in supporting my participation in numerous conferences and workshops, both nationally and internationally, has been invaluable in broadening my academic exposure and expanding my professional network. I would not be here today without your belief in my potential.

I am also deeply grateful to Professor David Bunch. Taking your classes was an incredibly rewarding experience, and the skills I gained from them have been essential to my Ph.D. work. Professor Alan Jenn has been an inspiration throughout this journey. Your mentorship in data analysis and presentation has played a pivotal role in my academic development. I have also benefited greatly from the opportunities to learn from Professors Patricia Mokhtarian, Susan Handy, Gil Tal and Miguel Jaller. A special thank you goes to my amazing colleagues, Dr. Yongsung Lee, Dr. Jai Malik, Dr. Junia Compostella, Dr. Mischa Young, Dr. Basar Ozbilen, Dr. Patrick Loa, Dr. Siddhartha Gulhare, Grant Matson, Jame Giller, Keita Makino, and Aurojeet Jena. Your unwavering support has been crucial to my research.

The past five years have been truly unique, especially as I navigated the challenges and uncertainties brought on by the COVID-19 pandemic. Despite these hurdles, it has been a period of immense personal growth, as I also embarked on the rewarding journey of building my family and becoming a mother. I am deeply grateful to my family and friends for their emotional and practical support. To my parents, thank you for your immense sacrifices in raising me, ensuring I receive a quality education, and encouraging me to pursue opportunities and life abroad. To my partner, thank you for your patience, understanding, and constant support as we balanced the demands of work, family, and life. And to my daughter, your presence and joy have been an endless source of motivation, reminding me every day of the importance of curiosity, perseverance, and love.

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1 Introduction

In recent years, the transportation sector has experienced significant disruptions driven by the emergence of new technologies. Alternative fuel vehicles (AFVs)[1] are providing consumers with more vehicle choices, and shared mobility services — such as ridehailing services operated by transportation network companies (TNCs) like Uber and Lyft, as well as micromobility options such as bike sharing and e-scooter sharing — are broadening mobility options available to travelers. These technology innovations are already reshaping vehicle ownership patterns, travel patterns and mode choices. California, in particular, has led efforts to promote more sustainable travel through policies aimed at reducing car dependence, encouraging multimodal travel, and accelerating the adoption of electric vehicles (EVs) in both privately owned and shared fleets. However, the extent of these changes and their potential to foster a more sustainable transportation system remain insufficiently understood. While some prior studies have examined factors that affect private vehicle ownership, fuel type choices, and the role of shared mobility, a more in-depth exploration is needed to understand the heterogenous effects of these factors across population groups distinguished by their attitudes, socio-demographic traits, and geographic contexts.

The adoption (and promotion of) AFVs has been a critical policy objective in California due to its potential social, economic, and environmental benefits. AFVs also offer long-term cost savings for consumers and transform the economic structure of mobility choices at the household level (e.g., Ogden et al., 2004). The California Zero-Emission Vehicle (ZEV) Action Plan, initiated in 2018, set ambitious targets of 1.5 million ZEVs (a mix of PHEVs, BEVs and FCEVs) on the road by 2025 and 5 million by 2030 (California Air Resources Board, 2020). In 2023, ZEVs accounted for 25% of new vehicle registration in California, totaling nearly 450,000 — a rate that significantly outpaces the national average of 9% (California Air Resources Board, 2024). Despite this progress, challenges persist. To further

[1] AFVs such as plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs) and hydrogen fuel cell electric vehicles (FCEVs) are motor vehicles that run on alternative fuels rather than solely petroleum fuels. PHEVs and BEVs are together referred to as plug-in electric vehicles (PEVs).

advance AFV adoption, policymakers need a thorough understanding of the factors affecting consumers decisions, as well as variations in preferences across population segments.

As society was beginning to shift towards cleaner vehicles, the outbreak of the COVID-19 pandemic in late 2019 disrupted individuals' activity-travel patterns, making it more challenging to predict vehicle ownership and fuel type choices. Private vehicle use surged during the pandemic (Krolikowski & Naggert, 2021) as people avoided shared transportation modes due to health concerns (Palm et al., 2024; Vega-Gonzalo et al., 2023; Wang et al., 2024; Zarabi et al., 2024). In the meantime, market uncertainty and an economic downturn also spared certain consumers from unnecessary hassles and expenses associated with purchasing or replacing cars (de Palma et al., 2022).

Shared mobility, especially ridehailing services offered by transportation network companies (TNCs), has grown increasingly popular over the past decade, although its use was heavily disrupted during the peak of the pandemic. Research on the impact of ridehailing on mobility patterns has yielded mixed findings. Some studies highlight its role in bridging mobility gaps for non-vehicle-owning households (Brown, 2019), substituting the use of private vehicles (Zou & Cirillo, 2021), and complementing public and active transportation (Sikder, 2019). Other studies suggest that ridehailing has contributed to increased vehicle miles traveled (VMT), congestion, and greenhouse gas (GHG) emissions (Erhardt et al., 2019; Wu & MacKenzie, 2021), while also reducing public transit ridership (Diao et al., 2021).

Ridehailing services have the potential to accelerate transportation decarbonization through fleet electrification, but significant gaps remain in understanding ridehailing drivers' vehicle fuel type choices and the factors that influence these decisions. According to the California Air Resources Board, the 2018 TNC vehicle fleets emitted 50% more CO_2-equivalent per passenger-mile traveled than the statewide average for passenger vehicles (California Air Resources Board, 2019). At the same time, studies have demonstrated that electrifying TNC fleets could significantly reduce emissions (Jenn, 2019; Sarasini & Linder, 2018; Sprei, 2018) due to the higher utilization of these vehicles. Accordingly, California introduced the Clean Miles Standard Program (Senate Bill 1014) in 2018, becoming the first U.S. state to regulate GHG emissions from the TNC fleets. By 2021, the state finalized a rule requiring 90% of TNC miles to be completed in ZEVs by 2030. While Uber and Lyft have pledged to transition to EVs, both companies reported that less than 1% of their drivers were driving ZEVs as of 2019 (Slowik et al., 2019). This slow progress highlights significant challenges in the electrification process, including the higher upfront costs of ZEVs (Rajagopal & Yang, 2020; Weiss et al., 2019) and the limited availability of reliable charging infrastructure (Moniot et al., 2019).

This dissertation brings valuable information to inform these processes and addresses key research gaps in the literature through four studies presented across four chapters (see Table 1-1). Broadly, it examines the roles of both privately owned and shared vehicles in shaping current and future mobility patterns, while also identifying potential pathways to facilitate the transition towards a more sustainable transportation system.

The **first study** (presented in **Chapter 2** of this dissertation) investigates the factors that impact the current and future adoption of AFVs in the privately owned vehicle market. These factors include latent attitudes, socio-demographic characteristics, and neighborhood effects (such as residential characteristics, accessibility to charging infrastructure, and level of exposure to AFVs). A joint integrated choice and latent variable (ICLV) model was estimated using a sample of 3,260 California residents drawn from the 2018 wave of the California Mobility Panel Study. Compared to standard discrete choice models, the ICLV model explicitly accounts for unobserved heterogeneity, enhances behavioral realism, and improves statistical efficiency by incorporating measurement scale responses on attitudes and perceptions. This approach provides richer behavioral insights and extends policy relevance of the model (Abou-Zeid & Ben-Akiva, 2014a; Vij & Walker, 2016). This study not only identifies the distinct factors impacting current and future AFV adoption respectively but also examines whether current user experience with AFVs can shape future adoption decisions.

The **second study (Chapter 3)** examines the factors that affect changes in household vehicle count (including additions, deletions, and replacements) for two timeframes: during and after the COVID-19 pandemic, i.e., from spring 2020 to fall 2023 and from fall 2023 to fall 2026. The study uses a panel dataset of 1,612 U.S. residents that participated in two waves of surveys conducted in spring 2020 and fall 2023. This dataset incorporates both retrospective and prospective self-reported information. The longitudinal dataset enables us to analyze individual attitudes, characteristics, behaviors, and choices over time and, moreover, life events and COVID-related health concerns. A joint ICLV model with two outcome variables was estimated to capture the changes in vehicle count among population segments with distinct latent attitudes, socio-demographic traits, and COVID-related factors. The study differentiates between replacing one or more vehicles while maintaining the same total and making *no changes to the vehicle fleet*. Additionally, the study explored the impacts of less-studied factors on vehicle count, including individual attitudes, life events, work arrangements and COVID-related health concerns.

The **third study (Chapter 4)** focuses on ridehailing users. I investigate the interrelationships among ridehailing use, travel patterns and multimodality among ridehailing riders, using a week-long GPS-based travel diary from 5,053 commuters in four major metropolitan areas in California. Using a latent class cluster analysis, I first classified respondents into four travel groups, each with varying levels of multimodality, based on their one-week trip frequencies across five travel modes for both commuting and non-commuting purposes. Each traveler group is characterized by unique sociodemographic and built-environment attributes. To enhance the representativeness of the findings for the California population, I incorporated weights into the model, which yielded more realistic results compared to an unweighted approach. I further explored the association between multimodality and ridehailing adoption/usage, by comparing the trip attributes (e.g., timing, location, and purpose) of 1,839 weighted ridehailing trips from the four traveler groups.

The **fourth study (Chapter 5)** examines the vehicle fuel type choices of ridehailing drivers. Ridehailing drivers are not a monolith, as this group encompasses both those who drive on a full-time basis as well as those who only drive on a part-time or an occasional basis. Moreover, some drivers may drive a vehicle that is specifically chosen for ridehailing work, while others may use their existing vehicle that can be used for both ridehailing work and to meet their household needs. Therefore, it is reasonable to hypothesize that drivers who obtained their vehicle with the intention to use it for ridehailing work may have quite distinctive characteristics and decision-making process. This study uses data from a web-based survey of ridehailing drivers in California conducted with support from Uber and Lyft, to understand the factors influencing the adoption of EVs for ridehailing work. Using data from 1,099 drivers, I estimated an ICLV model to (1) identify the factors motivating ridehailing drivers to obtain a vehicle, with or without the intention to use it for ridehailing work; (2) explore the factors impacting the vehicle fuel type choices for these two groups of drivers, including individual attitudes, socio-demographics, availability of charging infrastructure, and familiarity with incentives.

Table 1-1 Datasets and methodologies for research questions

	Research Questions	Dataset		Method	Outcome Variables/ Indicators	Chapter
		Survey	**Sample size**			
RQ1	What factors affect Californians' current vehicle fuel type choice and future interest in alternative fuel vehicles?	California Mobility Panel Study (2018 dataset with California sample)	3,260	Joint integrated choice and latent variable model with two outcome variables	- Current vehicle fuel type choice *[ICEVs, PHEVs, BEVs]* - The interest in alternative fuel vehicles in the future *[No, Yes]*	2
RQ2	What factors affect the changes and expected future changes in household vehicle count during and after the COVID-19 pandemic?	COVID-19 Mobility Panel Study (2020 and 2023 waves of panel dataset with US sample)	1,612	Joint integrated choice and latent variable model with two outcome variables	- Changes in vehicle count in the past (spring 2020 to fall 2023) *[Increase, Decrease, Replace, No change]* - Changes in vehicle count in the future (fall 2023 to fall 2026) *[Increase, Decrease, Replace, No change]*	3
RQ3	How do the adoption and use of ridehailing services vary among traveler groups with various levels of multimodality?	SACOG Travel Survey (2018) California TNC Study (2018-2019)	1,537 3,516	Weighted latent class cluster analysis	- Weekly trip frequency by various modes - Ridehailing adoption, usage, and trip attributes	4
RQ4	What factors impact the fuel type choices, and how do these factors vary across different ridehailing driver groups?	California TNC Driver Survey (2023)	1,099	Joint integrated choice and latent variable model with three outcome variables	- Whether the ridehailing vehicle is obtained with the intention of ridehailing work *[No, Yes]* - Ridehailing vehicle fuel type choice *[ICEVs, HEVs/PHEVs, BEVs]*	5

2 Deciphering the Factors Associated with Adoption of Alternative Fuel Vehicles in California[2]

2.1 Abstract

Promoting the use of AFVs[3] has become a long-term transportation strategy in California, which can bring a broad range of social, economic, and environmental benefits. Based on a sample of 3,260 California residents from the 2018 California Panel Survey, this study explores the impacts of latent attitudes, socio-demographic characteristics, and neighborhood effects on consumers' *current vehicle fuel type choice* and their *interest in purchasing or leasing an AFV in the future*. One joint ICLV model is estimated to understand the taste heterogeneity within different population segments. The results suggest that latent attitudes towards *environment, new technologies, car utilitarianism,* and *residential location preference* play critical roles in individuals' adopting new vehicle technologies. A range of socio-demographics, including age, race, gender, student status, education level, income level, household size, housing tenure, housing type and residential parking also make effects. Exposure to BEVs in both residential location and worksite has positive influence on AFV adoption, although public EV charging stations were not found to be an essential factor since survey respondents may mainly rely on home chargers. Moreover, the study suggests that individual's current user experience with AFVs has positive effect on their future interest in AFVs. Overall, based on current reported intentions, I estimate that the market's potential ceiling for AFV adoption could reach 41% of the adult population. Achieving higher adoption would likely require significant shifts in public opinion and changes in incentives and regulations. The findings offer guidance on crafting California's transport policy to promote AFV, regarding the heterogeneity of the population's preferences and attitudes.

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[2] This chapter is a short version of a journal paper (Iogansen et al., 2023): *Iogansen, X., Wang, K., Bunch, D., Matson, G., & Circella, G. (2023). Deciphering the factors associated with adoption of alternative fuel vehicles in California: An investigation of latent attitudes, socio-demographics, and neighborhood effects. Transportation Research Part A: Policy and Practice, 168, 103535. https://doi.org/10.1016/j.tra.2022.10.012.*

[3] Hybrid electric vehicles (HEVs) and flexible fuel vehicles (FFVs) are not considered as AFVs in this study.

2.2 Introduction

Policymakers in California have advocated for the use of AFVs for decades, going back to the original exploration of a 2% EV sales mandate in the late 1990s (Collantes & Sperling, 2008). Even though the initial introduction of AFVs would be hampered by high production costs and limitations on, e.g., the availability of refueling/charging infrastructure and driving range, AFVs would have advantages in, e.g., fuel operating cost, and potential convenience from home chargers. Moreover, new technologies with improved environmental benefits could be attractive to a segment of early adopters that would help initiate the dynamic process of market development. It was always well understood that a transition from incumbent conventional fuel vehicles to AFVs would not happen spontaneously and would rely heavily on policy interventions to support the innovation diffusion process during early stages of market development.

For policymakers to design and implement policies to support this market formation process requires a detailed understanding of what factors would influence individuals' adoption and usage of AFVs over the course of this process. This gave rise to many studies across an array of relevant academic disciplines. Most studies were conducted during a period when there were essentially no AFVs in the marketplace, requiring highly exploratory research approaches and methodologies that employ hypothetical vehicle descriptions (e.g., discrete choice experiments). Even now, some 13 years after the introduction of PEVs in 2021, the general population in most markets has very limited awareness and knowledge of PEVs, so there continues to be additional studies employing similar approaches. At the same time, the number of PEV offerings has increased in recent years, and a growing segment of early adopters has been purchasing and using them. These consumers have been targeted and extensively studied to understand in detail which factors contributed to their adoption decision (including the role of existing policy-related incentives), and how this segment differs from the general population. While this has been going on, researchers' interests have expanded to include other mobility options (e.g., ridehailing/sharing, car sharing, bike sharing, e-bikes, and e-scooters) including the possibility of self-driving (autonomous) vehicles.

Within this context, this study uses survey data from a snapshot in time (2018) of 3,260 respondents from California's adult population, which corresponds to a vehicle market much further down the AFV adoption curve than most other markets in the US. The survey is not a focused vehicle-specific survey with, e.g., discrete choice experiments incorporating detailed vehicle attributes. Rather, it is a general-purpose transportation/mobility survey covering a wide range of issues, but with detailed questions on attitudes, lifestyle, activities, and socio-demographics. The vehicle-related questions are limited to (i) information about the vehicle they currently use, and (ii) a question about their interest in ever leasing/purchasing an AFV in the future. There is no prior educational information giving definitions of terms, so their responses are based exclusively on whatever awareness, knowledge, and beliefs about AFVs that they had at the time.

When considering an individual's responses to the current adoption of and future interest in AFVs, there is little doubt that a standard statistical analysis will suggest that the two responses are interrelated (i.e., correlated). Therefore, the goal of this analysis is two-fold. The first is to identify the details of how specific factors affect consumers' *current vehicle fuel type choice* and *interest in purchasing or leasing a BEV/ FCEV in the future*, respectively. Specifically, theory suggests that some factors may have similar effects on both choices, while others may differ in important ways. Adequately addressing these factors supports the second goal: To ascertain the potential effect of an individual's experience with their current vehicle choice on their interest in a future BEV/Hydrogen FCEV. My approach is to estimate a hybrid choice model (HCM), or alternatively, ICLV model to identify the source of heterogeneous AFV preferences within the population, focusing on latent attitudes, socio-demographics, and residential characteristics. In addition, I augment the survey data with variables from external sources to investigate potential neighborhood and infrastructure effects.

The contribution of this study is threefold. First, I incorporate information on attitudes to capture what would otherwise be unobservable. The estimated latent factors explicitly account for the taste heterogeneity in the process of adopting AFV. Therefore, policymakers and advocates for new vehicle technologies could effectively respond to different population segments. Second, California has a larger number of AFV adopters, higher market share, and better infrastructure supplies than other states (California Air Resources Board, 2020; Shaheen et al., 2020), which provides an opportunity for a detailed assessment. The assessment results will offer valuable insights into other markets that are relatively lower in the penetration curves. Third, I compare the correlates of consumers' current choice and their future intention, revealing the importance of current user experiences on AFV adoptions.

The remainder of the chapter is organized as follows. Section 2.3 reviews relevant literature. Section 2.4 describes the dataset, provides preliminary analyses, and discusses mathematical details of the model framework. The model results are presented in Section 2.5. I conclude this chapter with discussions and policy recommendations in Section 2.6.

2.3 Literature Review

2.3.1 Factors Influencing the Adoption of AFVs

A variety of social science theories and approaches are applicable when understanding the adoption of AFVs. At one level, an AFV is just one more instance of a "vehicle", a product category where the core benefit is providing personal mobility over more-than-short distances. The technological implementation of such an offering may be evaluated by consumers based on a number of vehicle characteristics that have some impacts on overall preferences, such as purchase price and operating cost (Breetz & Salon, 2018; Daziano & Achtnicht, 2012; Falchetta & Noussan, 2021; Helveston et al., 2015; Musti & Kockelman, 2011; Potoglou & Kanaroglou, 2007; She et al., 2017; Tanaka et al., 2014) and driving range (Danielis et al., 2018; Liu et al., 2021).

Formally, when a consumer makes a vehicle purchase decision, they select from a set of competing alternatives, so discrete choice modeling has been a widely used methodology for obtaining quantitative measures of consumer preferences for vehicle characteristics. These types of applications typically include the identification of how preferences might vary as a function of consumer characteristics such as household income, age, gender, household size, educational level (Sovacool, 2009), so-called "observable heterogeneous preferences". Because until recently AFVs have not existed in the marketplace, discrete choice experiments using hypothetical vehicle descriptions have been employed. Although this approach has applications for existing products, it is especially relevant when estimating potential demand for new-to-the-world products with features or characteristics that are notably different from the status quo. A widely cited early application for California is by Bunch et al. (1993), and many similar studies have subsequently appeared addressing many different markets (Al-Alawi & Bradley, 2013; Axsen et al., 2010; Jensen et al., 2014; Lee et al., 2019).

Beyond such issues as consumer preferences and demographic segmentation, there are other features of transitioning from conventional fuel vehicles to AFVs that are critically important. AFVs adoption is frequently viewed through the lens of diffusion of innovation theory (Lee et al., 2019). However, there are some features that are notably challenging. First, the primary motivation for a transition to AFVs is the need for reduced emissions, which is a public good. Second, the services provided by AFVs are a very close substitute for those offered by an entrenched incumbent with cost advantages (i.e., conventional vehicles). These features mean that such a diffusion of innovation is highly unlikely to occur naturally: policy interventions, such as increasing gasoline taxes, purchase price subsidies, and tax exemptions are required (Al-Alawi & Bradley, 2013; Sierzchula et al., 2014; Soto et al., 2014, 2018, 2021). Third, purchases in this product category require a relatively infrequent expenditure on a durable good that represents a sizable portion of most household budgets (in contrast to, e.g., microwave ovens and smartphones). Finally, transitioning to AFVs is not simply a matter of switching vehicles. How these vehicles can be used is also determined by an additional non-vehicle feature:

refueling infrastructure, including availability, fuel type, location, and price, are essential to the successful adoption of AFVs (Al-Alawi & Bradley, 2013; Egbue & Long, 2012).

Aside from these factors, several other diffusion-related concepts are highly relevant. Initially introduced versions of a new product will be purchased only by a small group of early adopters who are highly motivated by an interest in new technology and unconcerned with the "risk" of trying a new and unproven product. Over time, other segments of the population gain awareness and exposure to the new product through, e.g., *social interaction* with those from segments who tend to adopt earlier (Jansson et al., 2017; Manca et al., 2020). In contrast to choices from among existing products with much higher familiarity, choosing to consider and evaluate new products relies more heavily on cognitive processes involving *perceptions* and *attitudes* (Wang et al., 2021), so-called "unobservable heterogeneous preferences".

Another aspect of market formation dynamics is that the products themselves go through cycles in which features are improved, manufacturing costs (and therefore prices) go down due to learning effects, and the number of offerings increases, along with differentiation that satisfies a wider range of consumer preferences.

2.3.2 Modeling approaches for studying the adoption of AFVs

There is evidence of considerable progress in modeling the adoption of AFVs. Earlier studies used cluster analysis to emphasize the importance of attitudes in behavioral decisions (Anable, 2005; Dallen, 2007; Jansson et al., 2009). Galván et al. (2016) employed a series of discrete choice models to analyze the factors that influence the demand for alternatively fueled buses in Colombia. To provide more realistic modeling results, Bolduc et al. (2008) adopted a hybrid choice modeling approach to understand the adoption of vehicle technologies. This approach incorporates attitudes and perceptions as latent variables. In line with this, Daziano & Bolduc (2013) introduced Bayesian methods to build the statistical model.

Hybrid choice modeling is a commonly used method for analyzing the adoption of new vehicle technologies. At the early stage of EV penetration, Glerum et al. (2014) estimated a hybrid choice model that accounts for attitudes in the decision-making process to forecast the future demand. Using the same approach, Jensen et al. (2013) analyzed the changes in individual attitudes and preferences after experiencing an EV in their daily life. They found that significant changes happened to the priorities on driving range, top speed, fuel cost, battery life, and charging locations. More importantly, they found that environmental concerns positively affect the preference for EVs. Loss aversion (Mabit et al., 2015) and latent habitual effect (Valeri & Cherchi, 2016) were also found to affect the adoption of AFV significantly. Kim et al. (2014) applied an expanded hybrid choice by simultaneously estimating the effects of social influences and latent attitudes on the intention to purchase EVs. Overall, the impact of social networks on purchasing behavior was not strong; however, it depends on the types of social networks (i.e., peers, friends, family, colleagues) and the level of market shares in these types of social networks. Some studies have also employed general structural equation models to study the adoption of AFV (Morton et al., 2016; Rezvani et al., 2018).

In this study, I employ a version of HCM/ICLV models which can incorporate psychometric latent factors (e.g., internal knowledge, opinion, perceptions, and attitudes) as explanatory variables, thus yielding a more behaviorally realistic model. It hypothesizes that both choice and attitudinal responses are influenced by the same latent factors, directly or indirectly, while at the same time, those latent factors themselves are affected by experience and external factors, such as the characteristics of the decision-makers. This method shares many similarities with previous studies (Bansal et al., 2021; Ghasri et al., 2019; Jung et al., 2021; Qian et al., 2019). For example, AFV literature has evolved so that attitudes related to environmentalism and interest in technology are frequently included in modeling frameworks and found to be related to AFV adoption. In most cases, these models are developed around discrete choice experiments for vehicle attributes. In this case, I limit consideration to whether respondents currently use a PHEV or BEV (in contrast to an ICEV), and also on their stated likelihood to consider an

AFV for a future purpose. An important feature of the analysis is that it estimates structural relationships to disentangle what would otherwise be highly correlated effects.

2.4 Data and Method

2.4.1 2018 California Panel Survey Data

The dataset used in this study was collected in 2018, as the second wave of data collection of a large longitudinal research project that investigates the impacts of emerging transportation technology and new mobility services on people's travel behavior and vehicle ownership within the State of California (Circella et al., 2019). The data collection used a mixed sampling method, generating over 4,000 complete responses through three channels: (1) A paper survey was mailed to a stratified random sample of 30,000 California residents; (2) A sample of 2,000 Californians was recruited via an online opinion company using quota sampling based on geography, neighborhood types, and key socio-demographics; and (3) Respondents from the 2015 data collection (N=1,975) were re-contacted through the same online panel. The data contains extremely rich individual-level information on socio-demographic traits, attitudes towards a variety of topics, current travel behavior, vehicle ownership and detailed information about the primary vehicle used (if any), access to all types of facilities (e.g., parking) and others.

To compensate for the non-response bias present in the raw data, a two-stage weighting process (cell-weighting + iterative proportional fitting) was implemented. The population target is based on the 2014-2018 American Community Survey 5-year estimates on eight variables including region, neighborhood type, age, gender, race-ethnicity, household annual income, presence of children and student/employment status. Overall, the weighted data is a good representation of the population in California. For more detailed information on weighting, please refer to the full journal paper. All descriptive analyses presented in this chapter are based on weighted data.

2.4.2 Current Vehicle Fuel Type Choice & Future Interest in AFVs

This study focuses on respondents who reported that either themselves or their household members owned or leased at least one vehicle. Respondents indicated the fuel type of the vehicle that they currently use ***most often*** (*single choice out of seven fuel type options*, including gasoline, diesel, HEV, PHEV, BEV, FFV and FCEV), as well as their interest in buying/leasing an AFV in the future (*multi-choices out of four fuel type options*, including HEV/ PHEV, BEV, FFV and FCEV). Gasoline, diesel, and flex-fuel vehicles were all categorized as ICEVs. There is only one hydrogen FCEV current user, so it was excluded from the analyses.

Figure 2-1 shows a simplified modeling framework for this study. For the *current fuel type choice*, ICEVs and HEVs were combined as conventional fuel vehicles. PHEVs and BEVs were separate since they have a number of distinctions in terms of vehicle features, user experience, requirements for infrastructure and policy regulations. The *future interest in AFVs* was aggregated into a binary choice (i.e., no interest/ have interest) based on their interests in BEVs or FCEVs, two fuel types that require the most "innovativeness" and are the main interests of California ZEV Mandate (California Air Resources Board, 2020). The current and future choices were modeled jointly, and their interrelationships will be discussed in the coming sections.

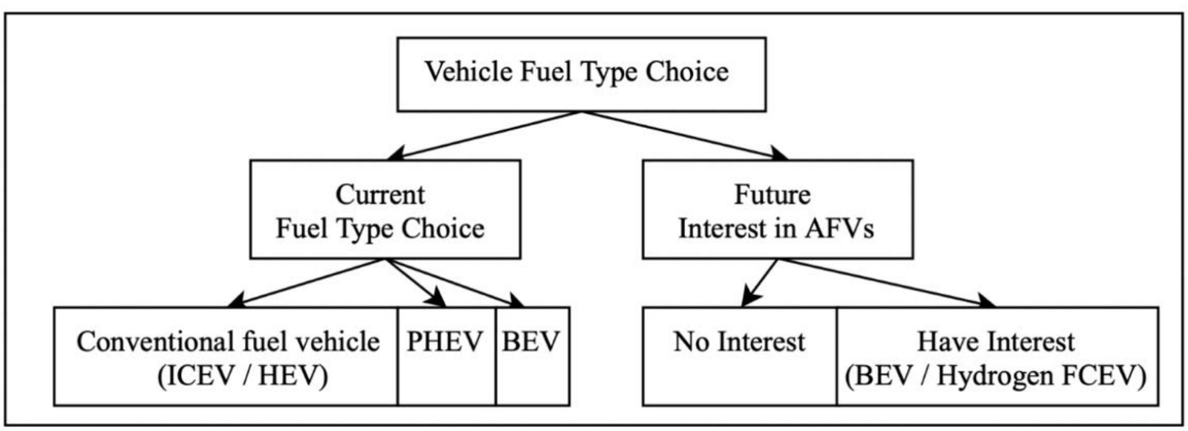

Figure 2-1 Modeling Framework

After data cleaning, the weighted sample of this study is 3,251. The weighted distribution of combined current and future fuel type choices is shown in Table 2-1. Unsurprisingly, conventional fuel vehicles were chosen by over 98% of the total sample as their most frequently used vehicle, and more than 60% showed no interest in AFV in the future. Most current AFV users, especially BEV users, will be much more open to AFVs in the future. Pearson's Chi-squared tests suggest that the future interest in AFVs is significantly correlated with current fuel type choice.

Table 2-1 Weighted distribution of combined current & future fuel type choice

Current Vehicle Fuel Type	**Weighted Sample (N)**	**Weighted Distribution (column-wise 100%)**	**Interest in purchasing/leasing an AFV in the future (row-wise 100%)**			
			No interest	**Have interest**		
				BEVs only	**FCEVs only**	**BEVs & FCEVs**
Conventional fuel vehicles	3,188	98.1%	60.7%	21.7%	2.5%	15.1%
ICEVs	*3,003*	*92.4%*	*62.0%*	*21.3%*	*2.3%*	*14.4%*
HEVs	*185*	*5.7%*	*39.1%*	*28.5%*	*5.9%*	*26.5%*
PHEVs	38	1.2%	32.7%	30.5%	0.0%	36.7%
BEVs	25	0.8%	6.7%	64.1%	5.9%	23.3%
Total sample	**3,251**	**100.0%**	**1,949**	**719**	**82**	**501**
% of total sample	**--**	**--**	**59.9%**	**22.1%**	**2.5%**	**15.4%**

2.4.3 Variables and Descriptive Analyses

(1) Latent Attitudes

To extract individuals' latent attitudes, I performed an exploratory factor analysis (EFA) based on 21 attitudinal statements from the survey (see Table 2-2). The *pro-environment* factor encompasses individuals' positive attitudes towards governmental environmental regulations as well as personal environmentally friendly lifestyles. The *tech-savvy* variable reflects individuals' proficiency with new technologies and their openness to new experiences. The *car-utilitarian* factor pertains to individuals' value on the pragmatic aspects of a vehicle, such as taking more seriously on its functionality instead of its brand. *Car-dependent* factor indicates individuals' dependence on and attachment to their vehicle in daily life. Finally, the *pro-suburban* factor manifests individuals' preference to live in suburban areas to gain more spacious houses, even at the cost of worse neighborhood services and public transportation. Based on Table 2-3 which compares the characteristics of users with different fuel type choices (row 1-5), current AFV users and potential adopters tend to be more pro-environment, tech-savvy, and car utilitarian. PEV users seem to share some commonalities but also have some differences in terms of attitudes. Those latent factors are hypothesized to have impacts on AFV adoption.

(2) Socio-demographics

Based on Table 2-3 (row 6-22), regarding the current fuel type choice, students, employees, those more highly educated, and with higher incomes are more likely to adopt an AFV than their counterparts. For the future interest, it is clear that a substantial amount of people from all socio-demographic categories are willing to shift to an AFV, and yet the differences are also observed. For instance, although most current AFV owners live in a household with annual income of at least $100,000, a sizable percentage of population among median- and low-income households have in fact shown their future interest in AFVs. Similar phenomenon exists among other population segments.

(3) Neighborhood Effects

a. Past Exposure to PEVs at Residential Locations and Worksites

To measure the impact of PEV exposure, I used the same data as Chakraborty et al. (2022). In short, the PEV exposure at the residential location was measured by the stock of PEVs within a 1-mile radius of the centroid of each census block group where respondents resided. The PEV exposure at the worksite was measured by the expected number of PEVs a regular commuter from each block group is exposed to at the worksite. These two variables were included in the model, aiming to capture the potential effects of social interaction with peers, neighbors, family, and coworkers. Table 2-3 (row 32-35) suggests that current PEV users and potential adopters have higher PEV exposure in their neighborhoods and worksites than others. I thus hypothesize that the higher the exposure, the stronger the positive peer effect on people’s EV adoption.

b. Density of Public EV Supply Equipment (EVSE)

The EVSE density was measured by the number of EV charging stations (combining Level 1, Level 2, and DC Fast Chargers) in each census block group where respondents resided, as plotted in Figure 2-2. The original geocoded location of each EVSE was collected from the Alternative Fuels Data Center (US Department of Energy, 2020). Previous studies have found that public chargers can compensate for the unavailability of home chargers and ease some concerns of car buyers (Axsen et al., 2010; Zou et al., 2020). My study included this variable to explore the effects of public EVSE network on consumers' propensity to own or lease PEVs. In fact, the survey data as shown in Table 2-3 (row 36) suggests that current PEV vehicle users are located in areas equipped with lower EVSE. This is potentially due to the fact that respondents in the data mainly rely on home chargers.

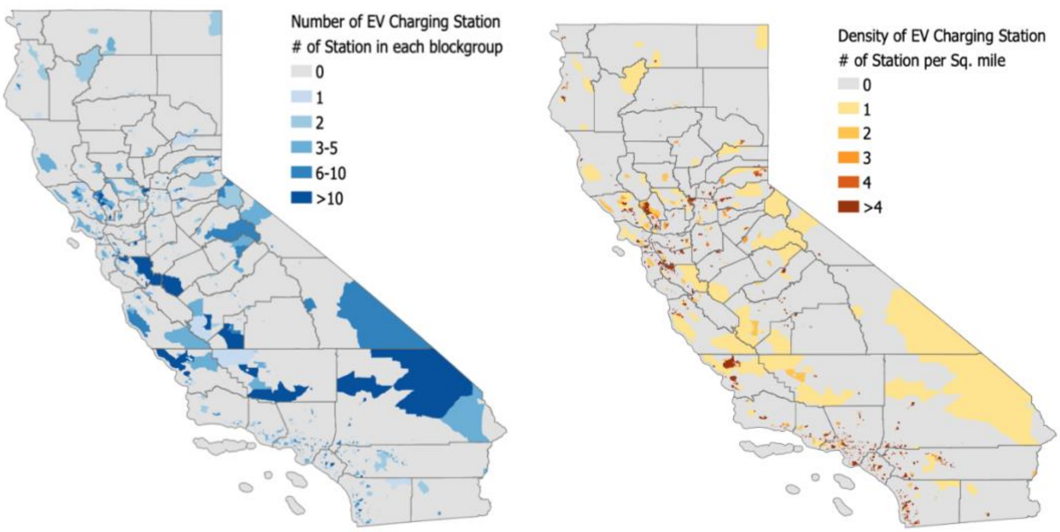

Figure 2-2 Count and density of EV charging station at the block group level

c. Accessibility to EVSE

The accessibility to EVSE is measured by the Euclidean distance (in mile) to the nearest EVSE from the home location of each respondent, which is one aspect of EV readiness. Even though only those PEV owners are using those facilities, I assume their existence can impact each respondent's decision-making and both the utility of their current and future fuel type choice. Based on Table 2-3 (row 37), the data suggests that individuals with better access to EVSE are more likely to adopt PEVs.

d. Residential Characteristics

Studies have shown that the availability of home chargers is influential in encouraging EV adoption (e.g., Hardman et al., 2018). Unfortunately, the survey did not directly collect information on whether respondents had any home chargers available. Four pieces of information related to residential ownership and built environment characteristics, including their neighborhood type (i.e., rural, suburban, urban), housing tenure (i.e., own, rent), housing type (i.e., house, apartment/condo/others), and residential parking (i.e., private parking, on-street parking) are included in my modeling. They are expected to capture some heterogeneous propensity of having reliable home chargers in the household. For instance, Lee et al. (2019) found that more than 80% of PEV adopters from 2012 to 2017 in California were homeowners. Also, charging in a single-family home, usually with a garage, is generally more convenient and allows EV owners to take advantage of incentives such as tax credit or rebates for home EVSE installation, and also obtain low and stable residential electricity rates for charging their vehicles in the long run. In comparison, charging at a multi-family home can be less reliable and more similar to the experience of using public chargers. Based on Table 2-3 (row 28-31), the data does suggest that individuals living in suburban/urban areas and owning a house with private parking are more likely to currently adopt PEVs.

Table 2-2 Results from exploratory factor analysis

	Latent Factors				
	Pro-environment	**Tech-savvy**	**Car-dependent**	**Car utilitarian**	**Pro-Suburban**
1. We should raise the price of gasoline to provide funding for better public transportation.	0.85				
2. We should raise the price of gasoline to reduce the negative impacts on the environment.	0.89				
3. I am willing to pay a little more to purchase a hybrid or other clean-fuel vehicle.	0.43	0.32			
4. The government should put restrictions on car travel in order to reduce congestion.	0.45		-0.32		
5. I am committed to an environmentally friendly lifestyle.	0.37				
6. Having Wi-Fi and/or 4G/LTE connectivity everywhere I go is essential to me.		0.54			
7. I like to be among the first people to have the latest technology.		0.65			
8. I would/do enjoy having a lot of luxury things.		0.38			
9. I like trying things that are new and different.		0.51			
10. Learning how to use new technologies is often frustrating for me.		-0.38			
11. Most of the time, I have no reasonable alternative to driving.			0.43		
12. My schedule makes it hard or impossible for me to use public transportation.			0.43		
13. I want to own a car.			0.53		
14. I prefer to be a driver rather than a passenger.			0.34		
15. I am fine with not owning a car, as long as I can use/rent one any time I need it.			-0.52	0.31	
16. To me, a car is just a way to get from place to place.				0.51	
17. The functionality of a car is more important to me than its brand.				0.48	
18. I prefer to minimize the material goods I possess.				0.45	
19. I prefer to live close to transit even if it means I will have a smaller home and live in a more crowded area.					-0.41
20. I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.					-0.43
21. I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.					0.65

Note: To determine the optimal number of factors, I relied on the Kaiser criterion of computing eigenvalues for correlation matrix. The rule is to keep the factor scores with Eigen values greater than one (Gorsuch, 1983). In terms of the type of rotation, I tried both orthogonal rotation and oblique rotation. After trying different specifications, five factors derived from 21 attitudinal statements using orthogonal rotation generated the optimal solution with better practical interpretation. Because factor axes remain orthogonal to each other, those factors are uncorrelated. The larger factor loadings correspond to a stronger relationship between the indicator and the corresponding latent factor.

Table 2-3 Comparison of user characteristics across different current vehicle fuel type choice and future interest in AFVs

	Variables	Categories	% of Case (column-wise %)	Current Fuel Type Choice (row-wise mean or %)			Future Interest in AFVs (row-wise mean or %)	
				Conventional fuel vehicles	PHEVs	BEVs	No Interest	Have Interest
	Latent Attitudes							
1	Pro-environment	(mean)	100.0%	-0.08	0.47	0.84	-0.24	0.19
2	Tech-savvy	(mean)	100.0%	-0.03	0.77	0.95	-0.23	0.31
3	Car-dependent	(mean)	100.0%	-0.09	0.24	-0.27	-0.10	-0.07
4	Car utilitarian	(mean)	100.0%	0.05	0.27	0.75	-0.11	0.31
5	Pro-suburban	(mean)	100.0%	-0.02	0.14	-0.62	0.10	-0.20
	Socio-demographics							
6	Age	18-34	24.6%	98.2%	1.1%	0.6%	58.9%	41.1%
7		35-54	36.0%	98.0%	1.4%	0.6%	54.4%	45.6%
8		>= 55	39.4%	98.0%	1.0%	1.0%	65.6%	34.4%
9	Race	Non-White/Caucasian	22.7%	97.1%	1.4%	1.5%	58.9%	41.1%
10		White/Caucasian	77.3%	98.3%	1.1%	0.6%	60.2%	39.8%
11	Gender	Not-Male	56.5%	98.1%	1.0%	0.9%	64.7%	35.3%
12		Male	43.5%	98.0%	1.4%	0.6%	53.8%	46.2%
13	Student status	Not-Student	83.7%	98.5%	0.8%	0.7%	61.2%	38.8%
14		Student	16.3%	95.6%	3.0%	1.4%	53.6%	46.4%
15	Employment	Unemployed	38.4%	99.0%	0.5%	0.5%	69.3%	30.7%
16		Employed	61.6%	97.5%	1.6%	0.9%	54.1%	45.9%
17	Education	Below college degree	53.0%	99.4%	0.4%	0.3%	67.4%	32.6%
18		College degree or above	47.0%	96.6%	2.1%	1.3%	51.5%	48.5%
19	Household income	< $50,000	41.7%	99.3%	0.2%	0.5%	68.4%	31.6%
20		$50,000 to $99,999	49.3%	98.0%	1.3%	0.7%	55.1%	44.9%
21		>= $100,000	8.9%	92.3%	5.1%	2.6%	47.5%	52.5%
22	Household size	(mean)	100.0%	2.80	3.33	2.82	2.78	2.85
	Residential Characteristics							
23	Neighborhood type	Rural	24.9%	99.0%	0.6%	0.4%	65.3%	34.7%
24		Suburban	43.9%	97.6%	1.4%	1.0%	58.0%	42.0%

25		Urban	31.2%	97.9%	1.3%	0.8%	58.4%	41.6%
26	Housing tenure	Rent	43.2%	99.2%	0.5%	0.3%	60.7%	39.3%
27		Own	56.8%	97.2%	1.7%	1.1%	59.3%	40.7%
28	Housing type	Apartment, condo, or others	26.0%	99.7%	0.3%	0.0%	63.9%	36.1%
29		Stand-alone/attached house	74.0%	97.5%	1.5%	1.0%	58.5%	41.5%
30	Residential parking	Unreserved, on-street parking or others	3.3%	100.0%	*0.0%*	0.0%	65.6%	34.4%
31		Private/reserved parking	96.7%	98.0%	1.2%	0.8%	59.7%	40.3%
	<u>Exposure to PEVs & PEV infrastructure</u>							
32	# of BEV exposure within one mile at residential neighborhood	(mean)	100.0%	84	149	133	77	98
33	# of PHEV exposure within one mile at residential neighborhood	(mean)	100.0%	78	115	129	71	91
34	# of BEVs exposure at worksite	(mean)	100.0%	19,404	32,496	32,624	18,872	20,836
35	# of PHEVs exposure at worksite	(mean)	100.0%	17,400	24,299	32,639	16,892	18,657
36	Density of EV charging station at residential location	(mean)	100.0%	53.49	7.65	12.36	55.35	48.57
37	Distance to nearest charging station at residential location	(mean)	100.0%	1.60	1.30	0.87	1.67	1.47

2.4.4 Modeling Approach

For this study, a logit-kernel-based ICLV model (Abou-Zeid & Ben-Akiva, 2014b; Ben-Akiva et al., 2002; Vij & Walker, 2016; Walker & Ben-Akiva, 2011) has been constructed to simultaneously model the effects of individual characteristics, latent perceptions/attitudes, residential built environment characteristics, and the local context of the EV market on two different choices of respondents: current vehicle fuel type, and interest in leasing/purchasing of a BEV/FCEV (i.e., "future interest"). The model includes two multinomial/binomial logit-kernel sub-models for current choice (ICEV, PHEV, BEV) and future interest (No, Yes), respectively.

As Equation (1) suggests, the utilities for competing alternatives in the discrete choice sub-models depend on observed and latent variables associated with the decision-makers. Choice is determined by random utility maximization, as Equation (4) indicates. This study assumes that socio-demographic characteristics influence choice not only through direct effects on utility, but also indirectly through the latent variables. These indirect effects occur via the structural equation (2), where each latent variable is expressed as a function of exogenous socio-demographic variables, including age, gender, race, education degree, student status, employment status, household size, and household income.

Equation (3) specifies the measurement equation, where the effects of unobservable latent variables are manifested in 21 indicator variables from measurement scales in the survey. The indicators represent additional information that allows identification and interpretation of the latent variables. Initial decisions about the number of latent factors and the structural and measurement equations specification are based on the results of the EFA discussed earlier. The final model specification depends on statistical testing and inference using estimates of candidate ICLV models.

As noted, the structural equation (2) and measurement equation (3) support the identification of (unobserved) latent variables through their relationship to both observed socio-demographics and indicators, and by design these latent variables are hypothesized to include substantial information related to (unobserved) latent utilities for both current fuel type choice and future purchase intent. As such, estimated model parameters yield useful behavioral insights. Moreover, this integrated model captures key underlying effects that cause observed choices for current fuel choice and future interest to be correlated, which opens the possibility for correctly isolating potential experience effects.

Utility specification:

$$u_{mnj} = B_m x_{nj} + \Gamma_m x_n^* + \epsilon_{mnj} \,,\ \epsilon_{mnj} \sim i.i.d.\,Gumbel \quad (1)$$

Structural equation:

$$x_n^* = As_n + v_n \,,\ v_n \sim N(0, \Phi) \qquad (2)$$

Measurement equation:

$$i_n = Dx_n^* + \eta_n \,,\ \eta_n \sim N(0, \Psi) \qquad (3)$$

Choice equation:

$$y_{mnj} = \begin{cases} 1, \text{if } u_{mnj} \geq u_{mnj'}, \forall j' \\ 0, \text{otherwise} \end{cases} \qquad (4)$$

If,

J_{mn} denotes the number of mutually exclusive alternatives *j* (*j* =1,…, J_n) that are available to individual n in choice situation m (i.e., current choice and future interest)

X denotes the number of observable features of each alternative,

K denotes the number of observable socio-demographic features of individual n,

M denotes the number of latent factors x_n^*,

R denotes the number of indicators (Likert-scale attitudinal statements),

Then,

u_{nj} is a (J×1) vector of the utility of alternative j for individual n,

x_{nj} is a (X×1) vector of observable features of each available alternative to individual n,

B_m is a (J×X) matrix of the unknown regression coefficients between each observable feature and each alternative in choice situation m,

x_n^* is a (M×1) vector of latent factors of individual n,

Γ_m is a (J×M) matrix of unknown regression coefficients between each latent factor and alternative in choice situation m,

ϵ_{mnj} is a (J×1) vector of random disturbances of unobserved component with i.i.d. Gumbel distribution,

s_n is a (K×1) vector of observable socio-demographic features of individual n,

A is a (K×M) matrix of the unknown regression coefficients between each socio-demographic feature and each latent factor,

v_n is a (M×1) vector of random disturbances with normal distribution $N(0, \Phi)$,

Φ is a (M×M) variance-covariance matrix,

i_n is a (R×1) vector of the level of the agreement to each attitudinal statement of individual n,

D is a (R×M) matrix of factor loadings indicating the relationship between each indictor and latent factor,

η_n is a (R×1) vector of measurement errors with normal distribution $N(0, \Psi)$,

Ψ is a (R×R) diagonal matrix with variance terms on the diagonal,

y_{mnj} is the final choice of individual n among alternative J.

Figure 2-3 illustrates the ICLV model for current fuel type choice and future interest with hypothesized relationship based on initial factor analysis (see Table 2-2) and regression models for the measurement and structural models. I use the *Apollo* library in R for performing maximum simulated likelihood estimation (Hess & Palma, 2019) using the Bunch-Gay-Welsch (Bunch et al., 1993) maximum likelihood estimation algorithm.

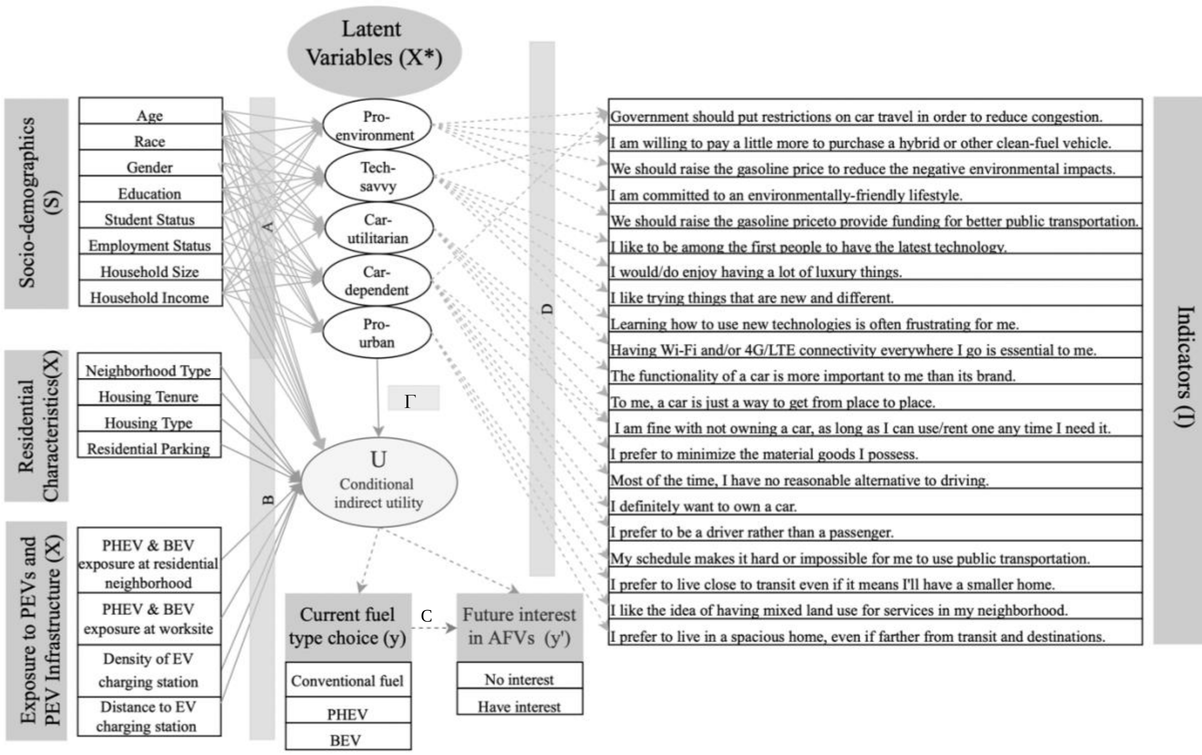

Figure 2-3 ICLV model framework

2.5 Results and Discussions

Table 2-4 shows the coefficients of each indicator in the measurement equation, which suggests the relation between each of the five latent variables and the corresponding indicators. They are comparable to the factor loadings from the EFA, and all are statistically significant[4].

[4] Indicators were standardized (mean-centered with a variance of one) to correspond to the structure of EFA. In addition to coefficients, standard deviations were also estimated but are not shown here to save space (they were all very close to one, as might be expected).

Table 2-5 shows the estimated coefficients for the structural equation, which confirms my hypothesis that exogenous socio-demographic attributes significantly influence people's perceptions and attitudes.

People who are younger, more highly educated, with higher incomes, and with a smaller household size are more *pro-environment* than their counterparts. Many of the above characteristics look alike among *tech-savvy* people, except that men, students, employees, and people with a larger household size are more *tech-savvy*. Non-white people are also more *pro-environment* and *tech-savvy*, this is consistent with some signs suggesting a potential digital transformation among the younger and a more racially diversified population (Enni et al., 2016). The findings for the *car-dependent* factor are consistent with expectations. People who are older, with higher incomes are more car dependent. In contrast, students, and those who are more highly educated are less car dependent. Regarding *car utilitarianism*, the pragmatic aspects of a vehicle seem to be less of a concern to males and high-income individuals, potentially because they are more driven by other aspects of vehicles, such as the representation of social status. At the same time, those who are older and more highly educated pay more attention to the pragmatic aspects of vehicles. Finally, in terms of residential location preferences, those who are white, have higher incomes and larger household sizes are more *pro-suburban*, while students, employees, people with higher education are less so.

These findings identify key relationships between observable population characteristics and underlying attitudes that would otherwise be represented as "unobservable heterogeneity" using standard discrete choice modeling approaches. This has potentially important policy implications because observable socio-demographics are more actionable when it comes to understanding how groups might react differently to different policies, and how policies might be designed, tailored, and efficiently targeted.

Table 2-4 Estimation results from the measurement equation

	Latent Factors									
	Pro-environment		Tech-savvy		Car-dependent		Car utilitarian		Pro-Suburban	
	Coe.	**t-stat.**	**Coe.**	**t-stat.**	**Coe.**	**t-stat.**	**Coe.**	**t-stat.**	**Coe.**	**t-stat.**
1. We should raise the price of gasoline to provide funding for better public transportation.	1.15	(57.11)								
2. We should raise the price of gasoline to reduce the negative impacts on the environment.	1.09	(52.35)								
3. I am willing to pay a little more to purchase a hybrid or other clean-fuel vehicle.	0.56	(25.84)	0.30	(12.93)						
4. The government should put restrictions on car travel in order to reduce congestion.	0.53	(22.36)			-0.38	(-14.49)				
5. I am committed to an environmentally friendly lifestyle.	0.39	(22.67)								
6. Having Wi-Fi and/or 4G/LTE connectivity everywhere I go is essential to me.			0.61	(25.17)						
7. I like to be among the first people to have the latest technology.			0.63	(25.27)						
8. I would/do enjoy having a lot of luxury things.			0.37	(16.19)						
9. I like trying things that are new and different.			0.37	(20.01)						
10. Learning how to use new technologies is often frustrating for me.			-0.52	(-20.68)						
11. Most of the time, I have no reasonable alternative to driving.					0.52	(12.56)				
12. My schedule makes it hard or impossible for me to use public transportation.					0.45	(9.66)				
13. I definitely want to own a car.					0.46	(19.10)				
14. I prefer to be a driver rather than a passenger.					0.36	(11.05)				
15. I am fine with not owning a car, as long as I can use/rent one any time I need it.					-0.65	(-17.85)	0.34	(9.00)		
16. To me, a car is just a way to get from place to place.							0.67	(18.10)		
17. The functionality of a car is more important to me than its brand.							0.50	(16.51)		
18. I prefer to minimize the material goods I possess.							0.39	(11.11)		
19. I prefer to live close to transit even if it means I will have a smaller home and live in a more crowded area.									-0.87	(-29.41)
20. I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.									-0.55	(-20.25)
21. I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.									0.58	(16.09)

Note: Statistics in the table represent coefficients and robust t-statistics. They are all statistically significant at 99% confidence level.

Table 2-5 Estimation results from the structural equation

		Latent Factors				
Social-demographic Characteristics	**Category**	**Pro-environment**	**Tech-savvy**	**Car-dependent**	**Car utilitarian**	**Pro-suburban**
Age	35-54	-0.16	-0.38	0.04	-0.06	-0.07
(base: 18-34)		(-2.65)***	(-5.74)***	(0.58)	(-0.82)	(-1.13)*
	>= 55	-0.21	-0.97	0.43	0.16	0.00
		(-3.57)***	(-13.20)***	(5.93)***	(2.32)**	(0.05)
Race	White/Caucasian	-0.12	-0.19	0.04	-0.07	0.16
(base: Non-white)		(-2.48)**	(-3.15)***	(0.69)*	(-1.16)	(2.77)**
Gender	Male	0.03	0.16	-0.04	-0.16	0.16
(base: Not-Male)		(0.71)	(2.94)***	(-0.68)	(-2.77)***	(2.59)***
Student Status	Student	0.19	0.50	-0.29	0.09	-0.33
(base: Not-Student)		(2.49)**	(5.88)***	(-3.39)***	(0.99)	(-4.34)***
Employment	Employed	-0.02	0.45	0.02	-0.04	-0.19
(base: Unemployed)		(-0.28)	(5.62)***	(0.26)	(-0.65)	(-3.44)***
Education	College or above	0.47	0.29	-0.32	0.29	-0.39
(base: Below college)		(9.67)***	(5.19)***	(-5.81)***	(4.68)***	(-7.07)***
Household Income	$50,000 to $99,999	0.09	0.07	0.03	-0.16	0.16
(base: < $50,000)		(1.66)	(1.04)	(0.47)	(-2.36)**	(2.46)**
	$100,000 or higher	0.16	0.30	0.26	-0.34	0.31
		(2.58)**	(4.10)***	(3.51)***	(-4.32)***	(4.38)***
		-0.05	0.04	-0.04	0.04	0.04
Household Size	(mean)	(-3.60)***	(2.57)**	(-2.35)**	(2.09)**	(2.33)**

Note: Statistics in the table represent coefficients, robust t-statistics, statistical significance, and confidence level: *10%, **5%, ***1%

Table 2-6 reports the results from the two logit models with interrelated dependent variables. People who are more *pro-environment* and *tech-savvy* are more prone to currently have PEVs as their most frequently used vehicle, and these attitudes similarly apply to leasing/purchasing AFVs in the future. Interestingly, the coefficient for car utilitarian has a positive, statistically significant coefficient for interest in a future AFV purchase. This indicates that, at the very least, there appears to be a perception among individuals with this attitude that AFVs will be feasible (utilitarian) choices in the future. It might even be that individuals have increased awareness and knowledge of such characteristics as lower operating cost, faster acceleration, and convenience of home recharging. Finally, *pro-suburban* is associated with the *current* use of BEVs. As discussed above, those individuals who are more likely to own a spacious home are in a better position to set up and use home charging infrastructure.

The model results demonstrate that there are many indirect effects of socio-demographics on the two dependent variables of interest. However, I found that, for current fuel type choice, direct socio-demographic effects were weak at best once indirect effects through attitudes were considered. In contrast, there are a number of direct effects on the interest in the future purchase of an AFV. Men, whites, people who are well educated, with higher-income, and non-students are more likely to have an interest in future purchase of an AFV than their counterparts. Similarly, very few direct effects associated with residential characteristics. As before, underlying attitudes associated with the choice of residential location might already capture key aspects of current fuel choice and future interest in an AFV. The strongest effect is that the choice of a PHEV is strongly associated with *having private/reserved parking*. There is also some indication that suburban location and living in a detached home could play a role (although these are not clearly significant). Moreover, these results show a statistically significant negative effect of home ownership on expressing future interest in an AFV. This result is inconsistent with my expectations and warrants further investigation.

My study attempts to identify neighborhood or peer effects, since these are an important part of the theory on diffusion of innovation. Exposure to BEVs at both the residence and workplace locations is found to be statistically significant in explaining current fuel choice, but the effects are limited. These exposure effects were not found to be statistically significant for the interest in the future purchase of AFVs. I also included exposure variables for PHEVs, but none were found to be statistically significant. Other variables from the supply side, including *density of EV charging station* and *distance to the nearest charging station* are not statistically significant for both current and future fuel choices in this study.

In the ICLV model, I included direct effects for current use of BEV and PHEV as explanatory variables for the interest in a future AFV purchase. The rationale is that having actual experience with either a PHEV or a BEV would increase the propensity to be interested in a future AFV purchase. Both coefficients were positive, with the BEV effect being larger than PHEV. This is consistent with findings from another study (Ling et al., 2021). Note that, when estimating effects of this type, there is a concern that a statistically significant result could be spurious, due to correlations induced by unobserved heterogeneity. In this case, the result could be misinterpreted as an experience effect. One reason for employing the ICLV methodology is to address such issues by using a modeling framework that incorporates a substantial amount of attitudinal information in a way that captures unobserved heterogeneity. As a test, I tested adding a normally distributed random error component with coefficients for PHEV, BEV, and interest in future AFV purchase (as might be used in mixed multinomial logit) to capture any residual underlying heterogeneity. The estimated model was not significantly different from the final model based on a likelihood ratio test (p=0.20).

Table 2-6 Results from discrete choice models

		Current Fuel Type Choice (Conventional fuel vehicles as the baseline)		**Future Interest in AFV (BEV/Hydrogen) (No interest as the baseline)**
Variables	**Categories**	**PHEV**	**BEV**	**Has interest**
Constants		-19.30	-7.38	-1.27
		(-23.24)***	(-5.18)***	(-4.24)***
Latent Factors				
Pro-environment		0.54	0.76	0.45
		(3.23)***	(3.87)***	(9.07)***
Tech-savvy		0.36	0.77	0.36
		(1.69)*	(3.23)***	(5.90)***
Car utilitarian		0.03	-0.16	0.14
		(0.14)	(-0.67)	(2.19)**
Pro-suburban		0.24	0.41	0.03

		(1.15)	(2.01)**	(0.55)
Socio-demographics				
Age	35-54	-0.22	0.77	0.15
(base: 18-34)		(-0.50)	(1.66)*	(1.14)
	55 or over	0.05	1.18	0.07
		(0.09)	(1.34)	(0.42)
Race	White	0.38	0.20	0.18
(base: non-white)		(0.90)	(0.46)	(1.76)*
Gender	Male	0.28	0.06	0.34
(base: female)		(0.91)	(0.20)	(4.19)***
Student status	Student	0.22	-0.91	-0.27
(base: non-student)		(0.44)	(-1.13)	(-1.93)*
Education	Bachelor or higher	0.88	1.00	0.29
(base: below bachelor)		(1.60)	(1.67)*	(3.20)***
Household size		0.16	-0.03	0.01
		(1.99)*	(0.22)	(0.31)
Annual household income	$50K - $100K	0.60	0.20	0.25
(base: below $50K)		(0.92)	(0.26)	(2.38)**
	$100K or over	0.68	0.82	0.54
		(1.08)	(1.08)	(4.48)***
Residential Characteristics				
Neighborhood type	Suburban	0.67	0.05	0.00
(base: Rural)		(1.29)	(0.09)	(0.00)
	Urban	0.42	0.54	-0.16
		(0.76)	(0.86)	(-1.25)
Housing tenure	Own	0.29	-0.04	-0.25
(base: Rent)		(0.73)	(-0.07)	(-2.44)**
Housing type	House	1.24	0.14	0.01
(base: Apartment, condo, or others)		(1.69)*	(0.27)	(0.14)
Residential parking	Private parking	3.31	0.09	0.09
(base: Unreserved, on-street parking or others)		(8.40)***	(0.08)	(0.83)
Exposure to BEVs				
# of BEVs within one mile at neighborhood		-0.001	0.003	0.0003
		(-0.35)	(1.73)*	(0.47)
# of BEV exposure at worksite	Medium	0.82	1.84	0.19
(base: low)		(1.19)	(2.01)**	(0.77)
	High	1.10	2.25	0.33
		(1.29)	(2.03)**	(1.06)
Current User Experience				
Current user	PHEV user	----	----	0.58
(base: Conventional fuel vehicle user)		----	----	(1.56)**
	BEV user	----	----	1.38
		----	----	(2.60)**
# of Observation			3,260 (Conventional: PHEV:BEV= 3172:47:41)	3,260 (No: Yes= 1765:1495)
LL(0, choice)			-3581	-2260
LL(final, choice)			-416	-2108

Note: Statistics in the table represent coefficients, robust t-statistics, statistical significance, and confidence level: *10%, **5%, ***1%.

Finally, the estimated final model can be used to produce in-sample predictions of potential AFV adoption (BEVs and Hydrogen FCEVs) for the whole market in the state of California by using weights created to match Census-based demographic statistics. The result of this calculation is that the percentage of the 2018 California population interested in an AFV purchase is estimated to be 41.4% (with a 98% confidence interval of 41.1% - 41.7%). Note that the survey did not specify a timeline when asking respondents' future interest, thus, I consider 41.4% an estimate of a potential ceiling for AFV adoption.

2.6 Conclusion

In this chapter, I constructed an ICLV model to identify factors that impact individuals' current and subsequent AFV adoption. The results suggest that individuals who are more *pro-environment* and *tech-savvy* are more likely to be currently using a PHEV or BEV, and that these attitudes will continue to play a role in developing an interest in purchasing an AFV in the future. Qualitatively, this finding is, of course, entirely consistent with other studies in other regions of the US and abroad (Jenn et al., 2018; Jin et al., 2020; Tanwir & Hamzah, 2020). However, the results also suggest that in 2018 many individuals who had not yet adopted an AFV had, nevertheless, reached a stage where, given their current state of awareness and knowledge, they expected to be interested in a future AFV purchase, especially among those who exhibit an attitude of car utilitarianism.

However, interestingly, individuals who are male, older than 55, and with higher income are less car utilitarian, and therefore these socio-demographic factors should have an indirect effect on lowering the interest in future AFV purchases. At the same time, being male, being college-educated and having higher income has a positive, direct effect on future interest (Carley et al., 2013; Hsu & Fingerman, 2021; Sovacool et al., 2018). However, it is noteworthy that in this study these factors lack statistical significance as direct effects for explaining current PHEV and BEV choices, once key attitudes (pro-environment, tech-savvy, and for BEVs, pro-suburban) have been considered. In examining the structural equations, these three demographic characteristics affect these attitudes in a variety of ways so that, while their net indirect effects might be consistent with increased AFV adoption, the relationships are complex.

Focusing again on future intentions, environmental concerns, interest in technology, and education, which have often been associated with early adopters, are continuing to play a role in this process. Perceptions of AFVs as high-priced alternatives may have played a role for Californians assessing their interest in future AFV purchases in 2018. Finding a way to lower the perceived purchase price of AFVs continues to be important. This finding is entirely consistent with recent decisions by the State of California to aggressively address issues of equity and the potential impact on disadvantaged communities of policies supporting a transition to AFVs. While there is a range of AFV financial incentives, subsidy policies, and income tax credits enacted by federal and local governments to encourage AFV buyers, many do not account for these concerns. Identifying equity issues concealed in those programs and developing policies to better target beneficiaries may lead to higher adoption across more consumer segments and increased social benefits overall (Liu et al., 2022).

My results also tend to confirm prior results for the current fuel type choices. I did not find a strongly significant *direct* effect of living in stand-alone/attached houses on current usage of PHEVs or BEVs (nor did this affect future interest). However, BEV ownership is related to a pro-suburban attitude that focuses on ownership of spacious homes. I did observe a strong direct effect of private/reserved parking for those using PHEVs most often, but no similar direct effect for BEV usage. Taken altogether, these results are consistent with the need for dedicated, private space for home charger installation. In contrast, it is common for residents in multi-unit dwellings to share space, such as parking or electrical infrastructure, which makes charger installation harder. One way of mitigating this problem is to provide increased access to public chargers, and this has generally been viewed as a high priority by policy makers at both the state and federal levels.

Having said this, I was unable to find direct statistical evidence of the impact of public chargers on PEV adoption in this study. At the same time, this is a challenging problem, and researchers have generally found empirical evidence for this linkage to be elusive, despite its assumed importance. An exception is Chakraborty et al. (2022), who used a different methodology employing very large datasets of vehicle counts from vehicle registration data. Other studies suggesting that public charging infrastructure is a stimulus to EV diffusion include Egnér & Trosvik (2018) and Schulz & Rode (2022). However, one caveat is that most of those studies were conducted in much more mature regions, such as Sweden and Norway. While California is the nation's largest market for EVs with about a third of the nation's public charging stations, the impact of those chargers on consumers and their payback periods are still largely uncertain. This study, based on survey data with a relatively few respondents who use PEVs, may have been limited in its ability to detect this relationship. However, future similar studies with a combination of larger sample sizes and increased penetration of PEVs might be more successful.

In a similar vein, I also explored the possibility of neighborhood and peer effects, which diffusion of innovation theory suggests is important in the dynamics of market creation. Specifically, theory suggests that direct exposure to newly introduced products will increase awareness and knowledge by those in direct, physical proximity, accelerating the likelihood of additional adoption. I introduced measures of PEV exposure linked to both residential location and their associated worksites. In this instance, I found statistical evidence that exposure to BEVs at both residential and worksite locations increases the chances of a respondent being a current BEV user. In contrast to Chakraborty et al. (2022), effects involving PHEV exposure were not significant. In any case, these results tend to support a major rationale for government policies supporting introduction of AFVs, i.e., that such policies can accelerate the dynamics of penetration, particularly those that are oriented toward enhancing awareness [e.g., encouraging more hands-on test driving either as a driver or passenger (Ling et al., 2021)]. Previous studies have shown evidence of changes in attitudes and perceptions toward AFVs after real-life experience with using them (Jensen et al., 2013, 2014).

Finally, using the modeling results combined with sampling weights, I project that 41.4% of the adult population may show interest in AFVs in the future, which can be viewed as the market's potential ceiling for AFV adoption. This suggests that there is still notable untapped potential to increase the market share of AFVs based on attitudes and perceptions of Californians in 2018. This is entirely consistent with the sales increases observed over the past four years. Moreover, my projections indicate that the penetration will most likely differ among different population segments, with current high-income PEV users leading the way. However, the survey did not specify a timeline when asking respondents' future interest in AFVs, and thus some individuals might answer this question based on their short-time expectations, while others might answer it based on their long-term expectations.

There are some limitations of this study. First, the survey asked respondents to report the fuel type of the vehicle that is "used most often." Because of range limitations and lack of charging stations, AFVs often play a specific and limited role in meeting a household's travel needs and may not necessarily be the "most used" vehicle. In fact, the data suggests that current AFV users are more likely to have more than one vehicle in the household. As such, the survey was not structured to capture the full role of PEVs in the population, but among those frequent daily users who would have the highest level of familiarity with the PEVs. Second, while I included an extensive list of variables in the model, as noted at the outset, I did not study the specific effects of vehicle features (such as purchase price, charging time, and driving range) which have generally been found to have substantial impacts on consumers' AFV adoption. However, most of these studies have relied on methodologies using hypothetical vehicle descriptions (e.g., discrete choice experiments). Instead, this study specifically relied on the current beliefs and expectations developed by respondents based on their actual experiences in an evolving market. The results and insights from this study can form the basis for future efforts that include the role of vehicle features, but within a context of real-world market experiences. Third, as noted previously, PHEV and BEV users only account for a small fraction of the sample, and thus the power of analysis for some items was restricted. With the growing uptake of AFVs in California, similar studies with a larger sample size can capture additional insight into the dynamics of market penetration over time. Finally, from the standpoint of survey design, some survey questions can be better designed to avoid potential ambiguity. For instance, HEVs and PHEVs were combined as "gasoline hybrid" vehicles in the survey when it asked respondents their future interest in AFVs. I recommend having them separate in the survey questions and modeling process in the future.

Acknowledgments

This study was funded by the National Center for Sustainable Transportation (NCST), which receives funding from the USDOT [grant number 69A3551747114] and Caltrans [grant number 65A0686 Task Order 005] through the University Transportation Centers program. Special thanks to Kailai Wang, David Bunch, Grant Matson, and Giovanni Circella, for their invaluable contributions as coauthors of this study. I extend my sincere gratitude to Farzad Alemi, Yongsung Lee, Ali Etezady, Leticia Pineda, Diego Bernal, Rosaria Berliner, Sung Hoo Kim, Junia Compostella, Jai Malik, Niloufar Yousefi, and Kate Tiedeman for their efforts on data collection and data cleaning to make this research possible.

3 Changes in Household Vehicle Count During and After the Pandemic – A Panel Data Analysis

3.1 Abstract

This paper investigates the factors affecting changes in household vehicle count, including additions, removals, and replacements, based on actual transactions in the past (spring 2020 to fall 2023) and also anticipated transactions in the future (fall 2023 to fall 2026). Using a two-wave panel dataset (n=1,612) collected with retrospective and prospective survey questions in the U.S. in spring 2020 and fall 2023, I explore a wide range of hypotheses concerning vehicle count dynamics over time. An integrated choice and latent variable model identifies the effects of latent attitudes, sociodemographic characteristics, life events, work arrangements and COVID-related health concerns on the changes in vehicle count. *Novelty-seeking* individuals were more inclined to alter their vehicle count (i.e., increase, decrease or replace) in the future. Younger individuals, households with children, and those experiencing an increase in the number of children or adults showed a higher likelihood of acquiring vehicles, likely in response to an evolving increase in travel demand. Transitions into the workforce and an increase in household income were also associated with increased likelihood of vehicle acquisition. An increase in commute frequency reduced the likelihood of vehicle shedding during the pandemic and also increased the likelihood of vehicle acquisition post-pandemic, likely due to a rebound in demand for non-commuting trips. COVID-related health concerns discouraged vehicle shedding during the pandemic. Finally, all else equal, households that increased vehicle count during the pandemic are likely to either increase, decrease or replace it again after the pandemic, while those who shed vehicles tend to reacquire them, and those who replaced vehicles are inclined to do so again in the future.

3.2 Introduction

The COVID-19 pandemic substantially disrupted people's activity-travel patterns. During the initial phase of the pandemic, countries around the world witnessed a dramatic reduction in travel by air, mass transit, and other shared modes due to the fear of virus transmission (Shamshiripour et al., 2020). By contrast, a number of studies have highlighted a growing reliance on private vehicles (Krolikowski & Naggert, 2021), with a large proportion of the population perceiving cars as the safest option for their daily travel (Palm et al., 2024; Vega-Gonzalo et al., 2023; Wang et al., 2024; Zarabi et al., 2024) and some of the former non-car owners have been compelled to buy or lease one to avoid using mass transportation (Palm et al., 2024; Vega-Gonzalo et al., 2023). Moreover, the automotive industry struggled to meet the increased demand due to a substantial decline in vehicle production and delivery during the pandemic, when manufacturers faced disruptions due to business shutdowns, international supply chain disruptions, and shortages of raw materials amid the pandemic (Krolikowski & Naggert, 2021). This resulted in a decline in new automotive sales in the United States (Marina et al., 2022), and a boom in used car sales during the pandemic (Rosenbaum, 2020). Such market uncertainty and the economic downturn may have also spared certain consumers from unnecessary hassle and expenses associated with purchasing or replacing cars (de Palma et al., 2022).

Policymakers, auto manufacturers, and related businesses all seek to understand the ways that the pandemic has affected consumer behavior regarding vehicle ownership. However, serious gaps exist in our knowledge about these topics. First, although vehicle ownership choices have been well-studied before the pandemic, limited research has focused on the temporary and longer-term changes during and after the pandemic in the U.S. Second, many studies employ cross-sectional data (Klein & Smart, 2017) or pseudo panel data (Anowar et al., 2016), which do not allow direct examination of changes for the same households over time. Those types of data are also limited in their ability to capture the impact of life events (e.g., relocating to a new area, starting, or leaving a job) critical to understanding the underlying reasons behind decisions in vehicle ownership (Clark et al., 2016; Li, 2024). Third, to the best of the authors' knowledge, no prior study has modeled how past changes in vehicle ownership might directly impact future vehicle ownership decisions under conditions like those experienced during a pandemic (so-called "state dependence"). For example, all else equal, households that reduced their travel demand during the pandemic and shed vehicles may now have a higher likelihood of acquiring a vehicle in the future to accommodate increased travel needs in a post-pandemic era. Note that another important concept in dynamic modeling is “heterogeneity”, which refers to differences across individuals that are stable over time and are not influenced by prior choices. As suggested by previous papers (Kitamura & Bunch, 1990), in reality, decisions on vehicle holding often involve both state dependence and heterogeneity. I hope the modeling framework I proposed below could also help account for the heterogeneity by explicitly modeling individual attitudes.

To address these research gaps, this study analyzes a two-wave panel dataset collected in the U.S. to simultaneously investigate households’ changes in vehicle count in two time periods: *actual changes in the recent past* from March 2020 (i.e., measuring vehicle count at the start of the pandemic) to July/August 2023 (i.e., fall 2023), and *expected changes during the next three years* from July/August 2023 to July/August 2026 (i.e., fall 2026). In doing so, I look at four types of changes: (1) *increase* in the number of vehicles, (2) *decrease* in the number of vehicles, (3) keep the same total but *replace* one (or more) vehicle(s), and (4) make *no change* to the vehicles owned by the household. With an integrated choice and latent variable (ICLV) model, I identify factors affecting the changes in vehicle count, with a focus on individual attitudes (e.g., tech-savviness), socioeconomic and demographic (SED) characteristics, life events (e.g., starting a job), work arrangement (e.g., adopting remote work schedule), and COVID-related health concerns.

The remainder of this chapter is organized as follows. Section 3.3 synthesizes prior research on the topic. Section 3.4 describes the data, provides descriptive analyses, and presents the model framework. Section 4.5 highlights the model results and discusses the findings from the study. Finally, Section 3.6 concludes with policy implications and future research.

3.3 Literature Review

Scholars have extensively investigated the determinants of vehicle ownership decisions prior to the pandemic. Some studies analyzed vehicle ownership *at one given timepoint*. Sociodemographic and economic (SDE) characteristics and spatial attributes have been found to be associated with vehicle ownership (Macfarlane et al., 2015; Nobil et al., 1997; Prevedouros & Schofer, 1992; Train, 1993). Lifestyle, attitudes, and psychological factors also play significant roles (Choo & Mokhtarian, 2004; Wu et al., 1999), with *pro-car* attitude increasing ownership and *pro-environment* attitude decreasing it (Flamm, 2009; Lavieri et al., 2017). The adoption of online shopping and remote work was found to be associated with fewer household vehicles (Blumenberg et al., 2021).

Most studies examining *vehicle ownership changes over time* analyzed cross-sectional data. Lavieri et al. (2017) highlighted that multi-car households tend to make vehicle transactions more often. The presence of children is associated with an increase in vehicle ownership. Life events, such as changes in household composition, and residential location, significantly influence vehicle ownership decisions (Scheiner & Holz-Rau, 2013). Individuals with loss aversion tend to experience a greater psychological resistance to giving up vehicles (Grush & Niles, 2018). In addition, changes in vehicle ownership are closely tied to the access to alternative travel options. For instance, access to affordable and efficient public transportation systems, along with new mobility services such as carsharing, ridehailing, and micromobility, reduce the need for vehicle ownership (Blumenberg et al., 2021; Cullinane, 2002; Y. Liu & Cirillo, 2015).

It has become widely recognized that behavioral models based solely on cross-sectional data have inherent limitations (Dougherty, 2006; Kitamura & Bunch, 1990). However, dynamic panel models of vehicle ownership remain limited due to the scarcity of panel datasets. Using the four-wave British Household Panel Survey (1993-1996), Hanly & Dargay (2000) applied a latent regression model to demonstrate that current vehicle count is impacted by past vehicle count due to habit persistence or loyalty (i.e., the “Feedback Effect”). Yamamoto (2008) estimated a hazard-based duration model on a 15-

wave household panel data, showing that life-course events act as catalysts for changes in vehicle ownership. Similarly, Goodwill (1993), using UK panel data, found that income, age, previous vehicle ownership, and life-course events between survey waves are associated with current changes in vehicle ownership. Hanly & Dargay (2000) as well as Fatmi & Habib (2016) further highlighted that the effects of life events vary substantially across population segments, with changes in vehicle ownership often taking several years to materialize – a pattern consistent with durable goods acquisition behaviors (Mannering & Winston, 1985).

The COVID-19 pandemic has significantly reshaped many aspects of individuals' lives, including work arrangements (Iogansen et al., 2024), time use (Batur et al., 2023), travel behavior (Wang et al., 2024; Zarabi et al., 2024), and participation in in-person and online activities (Chowdhury et al., 2024; Matson et al., 2022). While some of these impacts were temporary, many are expected to have long-lasting effects. Numerous reports have discussed changes in vehicle sales and vehicle ownership trends during recent years. However, rigorous scientific studies on this topic remain limited.

The pandemic likely deterred some consumers from intending to purchase a vehicle due to some financial factors (Coibion et al., 2020). Rising car prices and housing expenses during the pandemic have also been reported to negatively affect vehicle acquisition among U.S. residents (Thakuriah, 2024). The same study shows that, conversely, government-issued economic stimulus funds increased their odds of obtaining a vehicle.

During the pandemic, individuals appeared to place greater value on the convenience of private cars, particularly the ability to travel spontaneously whenever and wherever needed (Moody et al., 2021). The perceived safety of private cars also became more important compared to the pre-pandemic period (Wang et al., 2024). In line with these findings, Palm et al. (2024) found that individuals who had contracted COVID-19 or lived with someone who had were more likely to purchase a vehicle.

Studies also indicate that the vehicle ownership changes during and after the pandemic varied across different population groups. The pandemic appeared to induce more car use and to increase the intention to purchase vehicles, particularly among individuals who were less car dependent prior to the pandemic, such as younger individuals and frequent transit riders (Palm et al., 2024; Vega-Gonzalo et al., 2023). Conversely, minorities, low-skilled workers, and residents of multi-family dwellings were less likely to increase their vehicle ownership. High-income, well-educated teleworkers were found to temporarily reduce their car use to a larger extent, while low-income individuals tend to maintain similar levels of car use.

While previous studies provide valuable insights into how socioeconomic factors, health concerns and economic conditions impacted vehicle ownership behavior, none have analyzed longitudinal data to explore changes in vehicle ownership across multiple timepoints. Additionally, few studies have incorporated attitudes and life events into their analyses, both of which are critical for understanding the underlying motivations towards vehicle ownership decisions. This study seeks to address these gaps.

3.4 Data And Method

3.4.1 COVID Mobility Surveys

This study uses survey data collected through a COVID-19 Mobility Study, with aims to provide insights into the short-term and long-term impacts of the pandemic on consumer behavior and mobility decisions in the U.S. To achieve this, the team designed and distributed four surveys with a rotating panel structure during the pandemic, with the first survey conducted in spring 2020 (May-August 2020, n=13,658), the second in winter 2020 (December 2020-January 2021, n=7,983), the third in fall 2021 (August-October 2021, n=14,084) and the fourth in fall 2023 (September-December 2023, n=6,469). At the time of writing, an additional wave of data collection is planned for Spring 2025. The mobility panel study also benefits from previous rounds of data collection conducted before the pandemic, in 2015, 2018 and 2019, in California and other selected regions of the U.S., with some respondents participating in multiple waves. Additional details about the project and the various waves of data collection are available on the project website (https://postcovid19mobility.ucdavis.edu), as well as in existing project reports (Circella et al., 2023; Ozbilen et al., 2024) and published journal papers (Compostella et al., 2023; Iogansen et al., 2024; Matson et al., 2023).

For all surveys, the team used a combination of sampling and recruitment approaches to reach a broader and more diverse pool of participants as well as reduce selection bias. These approaches included: (1) recontacting survey-takers from the previous survey waves in the project; (2) recruiting new participants via an opinion panel with a quota sampling method; (3) recruiting new participants via convenience sampling through posts on social media, professional email lists, local listservs, and personal connections; and (4) in fall 2021 and fall 2023, also inviting California residents via stratified random sampling and having them participated in the study either with a printed questionnaire or through an online survey. A mix of these approaches allowed us to offset known shortcomings of each approach and also recruit segments of population who are challenging to reach.

Each wave of the data collection collected detailed information on respondents' SED traits, technology use, online shopping habits, transportation mode use, vehicle ownership, and major life events that occurred prior to and during the pandemic. The surveys also included a series of attitudinal statements on various topics such as environment concerns, lifestyle choices, and car usage. To better capture changes during and after the pandemic, some questions in the surveys elicited responses for both the present (i.e., at the time of data collection), the past (via retrospective recall), and the future (via expectation) situations.

The present study focuses on a cohort of 1,612 longitudinal respondents who participated in both the spring 2020 and fall 2023 surveys in the U.S. Compared to the US population, this longitudinal sample has a lower representation of younger individuals, males, non-White and Hispanic individuals, and those with lower income levels. Consistent with findings in existing literature on panel studies, these survey participants are either more challenging to reach initially (Stempowski, 2023) or generally have lower retention rate for subsequent surveys (Satherley et al., 2015; Van Wissen & Meurs, 1989; Wang et al., 2023). Given the unique characteristics and limited sample size of the longitudinal dataset, I have opted not to apply weights to adjust for these deviations from the US population characteristics.

3.4.2 Dependent and Independent Variables

Figure 3-1 presents a set of key variables, collected from the spring 2020 and fall 2023 surveys and grouped by several reference timepoints. Self-reported changes in household vehicle counts are the choice outcomes of interest. Factors impacting these choices include attitudes, SED characteristics, as well as changes in SED characteristics and life events between the two timepoints. The final model analyzes the color-coded variables shown in this figure.

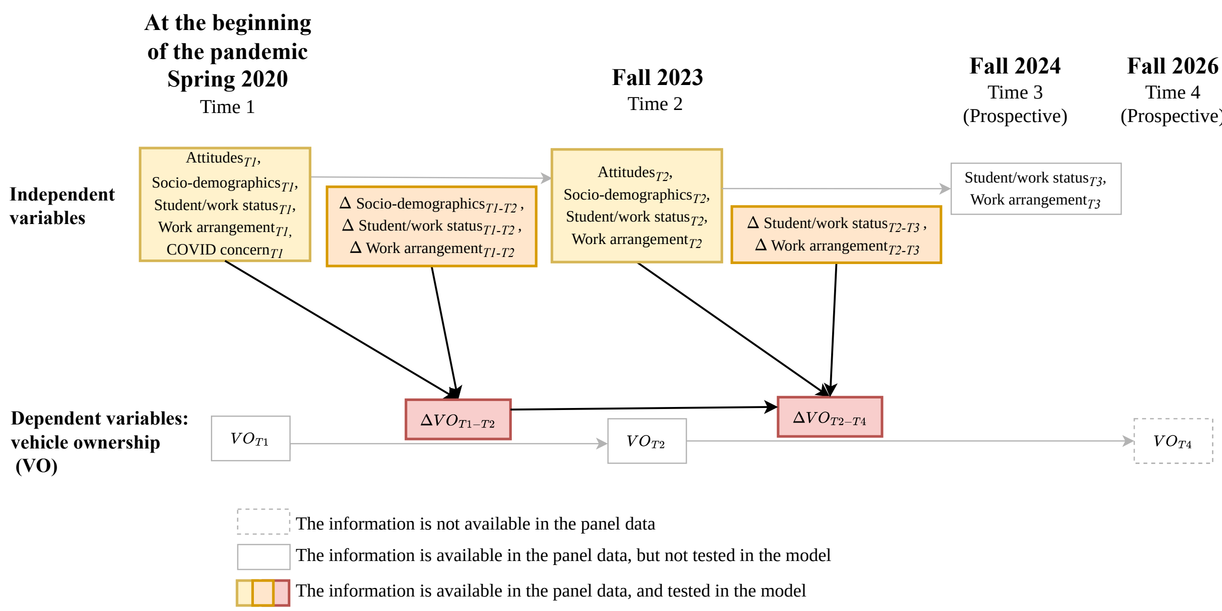

Figure 3-1 Key variable groups by timepoint

This study focuses on two dependent variables: (1) the past changes in vehicle count from the beginning of the pandemic (spring 2020) to fall 2023, and (2) the expected future changes in vehicle count over the next three years (fall 2023 to fall 2026). The two dependent variables were obtained from the fall 2023 dataset and validated using information about actual household vehicle ownership collected in the spring 2020 vs. fall 2023 surveys. As illustrated in Figure 3-2, between the start of the pandemic and fall 2023, 7.3%, 7.4% and 23.6% of respondents reported adding, shedding, or replacing vehicles, respectively. Looking three years ahead, 7.8%, 4.2% and 32.8% of respondents expected to increase, decrease, or replace their vehicles, respectively. Notably, the proportion of individuals replacing vehicles has been, and is projected to remain, higher than those adding or shedding vehicles. While past trends show a nearly equal proportion of individuals reporting they had increased or decreased their number of vehicles in the household, future expectations reveal a larger share of individuals planning to increase (7.8%) rather than decrease (4.2%) their household vehicle count.

I hypothesize that changes in vehicle count may be directly impacted by household dynamics, such as individuals moving in or out of the household and bringing or taking their vehicles with them. To account for this potential confounding factor, Figure 3-3 presents the same trends as Figure 3-2 but focuses only on households that maintained the same composition (i.e., the same number of adults and children) during the study period. As expected, the proportion of individuals who altered their vehicle count (including increases, decreases and replacements) in Figure 3-3 is lower than Figure 3-2.

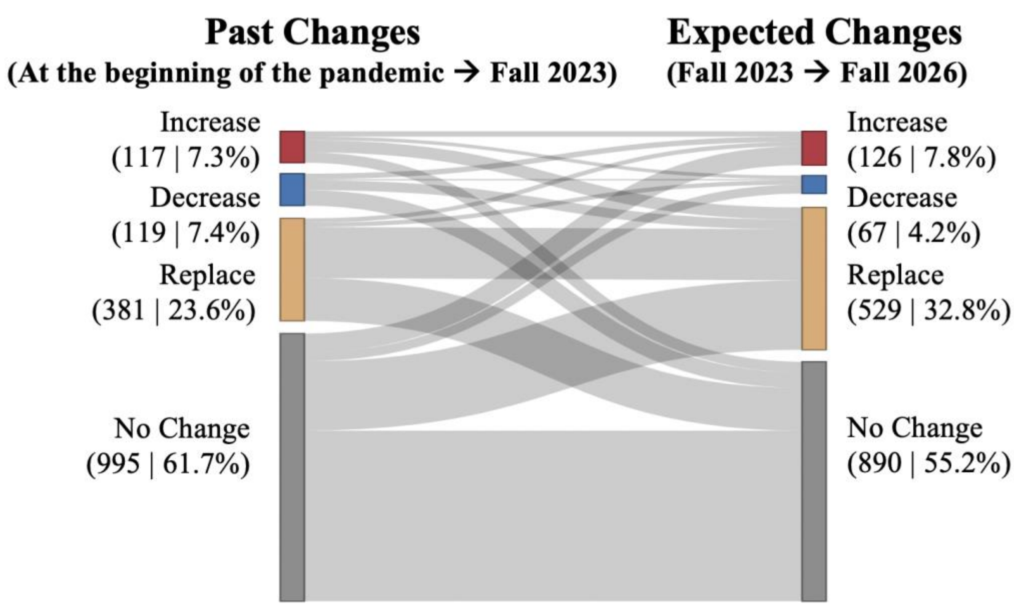

Figure 3-2 Past and expected future changes in household vehicle counts (n=1,612)

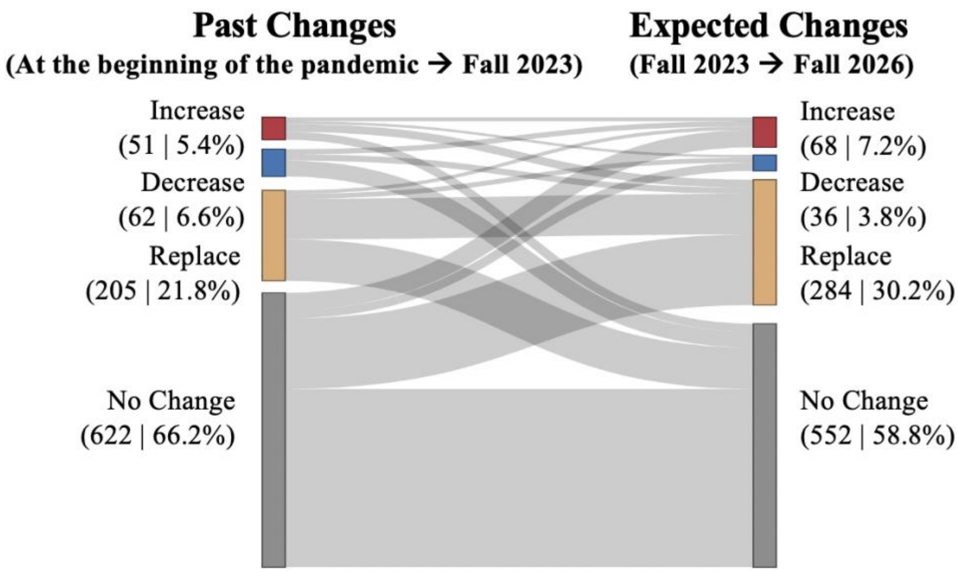

Figure 3-3 Past and expected future changes in household vehicle counts, for households that maintained the same composition (n=940)

We now discuss the variables used in this study to explain the recent and expected future changes in household vehicle count. Beyond standard SED characteristics (e.g., age cohort, gender, ethnicity, race), I explore a range of additional factors, including attitudes, life events, work arrangements, and COVID-related health concerns. Table 3-1 and Table 3-2 presents the summary statistics of all variables tested in the model. Note that some variables are available for only one timepoint.

I measured attitudes by analyzing responses to 18 attitudinal statements (rated on a five-point Likert-type scale from "strongly disagree" to "strongly agree"), collected at two timepoints. Using two exploratory factor analyses (EFA) with "promax" rotation, these statements were distilled into six underlying psychological constructs. The *pro-environment* factor reflects support for environmental regulations that raise the cost of driving to mitigate the negative impacts of transportation on the environment and fund better public transportation. The *pro-driving* factor captures a preference towards owning a vehicle and the enjoyment of driving. The *pro-active* factor highlights the value placed on active lifestyle through regular walking and exercise. The *novelty-seeking* factor indicates familiarity with and interest in new technologies and new experiences. The *car-captive* factor represents dependence on vehicles due to limited access to alternative travel modes and inconvenient schedules. Finally, the *pro-urban* factor reflects a preference for neighborhoods prioritizing urban amenities over spacious housing.

I examined various life events and their potential impact on vehicle counts. Changes in educational attainment and student/work status may influence activity/travel patterns, as commuting used to account for 15% of daily trips (before the pandemic), with 91% of workers using personal vehicles (Bureau of Transportation Statistics, 2017). From spring 2020 to fall 2023, 12.0% of respondents transitioned from being non-workers to workers, indicating employment recovery after pandemic-related job losses. Similarly, 27.9% reported income increases compared to 11.7% reporting declines. Further, more respondents anticipated starting or resuming work by fall 2024 than those planning to leave the workforce. Changes in household composition, such as shifts in the number of children (under 18), adults (18-64), or older adults (65 or over), may also impact vehicle needs. Studies have demonstrated that households often add or replace vehicles to accommodate changing needs associated with children (Lavieri et al., 2017). Finally, residential relocation, particularly when accompanied by significant changes in built environment characteristics, is expected to affect vehicle reliance. For instance, moving from rural to urban areas may lead to shedding vehicles due to better access to jobs and destinations. The adoption of hybrid and remote work arrangements likely impacts commuting frequency and vehicle needs. Notably, between spring 2020 and fall 2023, respondents reduced monthly commuting days by an average of 2.1 and increased remote working days by 3.4. Last but at least, I hypothesize that individuals with greater COVID-related health concerns may be more inclined to increase or maintain their vehicle count, driven by fears of shared travel modes.

After careful consideration, I chose to not include certain variables in the model. For instance, past vehicle count is highly correlated with recent changes in vehicle count, making it a strong explanatory variable. However, vehicle count in the past, as an outcome of various other factors, may absorb much of the explanatory power and statistical significance, limiting the insights into how other factors influence current and future vehicle count. Additionally, trip frequency and mode use are closely related to changes in vehicle count, but their bidirectional relationship could introduce endogeneity (Goodwin & Mogridge, 1981) if included as explanatory variables.

Table 3-1 Past and future changes in vehicle count by various characteristics at one timepoint

				Past Changes in Vehicle Count (spring 2020 to fall 2023)			
Variables	**Categories**	**n**	**% / mean**	**Increased 117 7.3%**	**Decreased 119 7.4%**	**Replaced 381 23.6%**	**No change 995 61.7%**
General Attitudes[1]							
Pro-environment			0.00	-0.05	-0.08	-0.10	**0.05**[5]
Pro-driving			0.00	**0.20**	-0.01	0.18	-0.09
Novelty-seeking			0.00	**0.47**	-0.23	0.16	-0.09
Pro-active			0.00	0.03	-0.20	**0.07**	-0.01
Car-captive			0.00	0.17	0.19	**0.26**	-0.12
Pro-urban			0.00	-0.21	-0.24	-0.11	**0.10**
SDE Characteristics							
Age cohort[2,3]	Millennials or younger (after 1980)	397	24.6%	22.0%	**40.2%**	21.0%	27.8%
	Generation X (1965-1980)	478	29.7%	27.7%	**44.4%**	22.7%	32.3%
	Baby Boomers or older (before 1965)	737	45.7%	50.3%	15.4%	**56.3%**	39.9%
Ethnicity[3]	Non-Hispanic/Latino/Spanish origin	1465	90.9%	88.0%	**93.3%**	90.0%	91.3%
	Hispanic/Latino/Spanish origin	147	9.1%	**12.0%**	6.7%	10.0%	8.7%
Race[3]	Non-white	371	23.0%	21.4%	16.8%	22.0%	**24.3%**
	White	1241	77.0%	78.6%	**83.2%**	78.0%	75.7%
Gender[3]	Not-Female	629	39.0%	**47.0%**	33.6%	38.1%	39.0%
	Female	983	61.0%	53.0%	**66.4%**	61.9%	61.0%
Education attainment	Lower than bachelors	526	32.6%	31.6%	33.6%	27.0%	**34.8%**
	Bachelor or higher	1086	67.4%	68.4%	66.4%	**73.0%**	65.2%
Student status	Not a student	1517	94.1%	90.6%	**95.8%**	93.4%	94.6%
	Student	95	5.9%	**9.4%**	4.2%	6.6%	5.4%
Work status	Non-workers	733	45.5%	29.9%	**57.1%**	38.3%	48.6%
	Workers	879	54.5%	**70.1%**	42.9%	61.7%	51.4%
Possess of a driver's license	No	53	3.3%	1.7%	1.7%	0.8%	**4.7%**
	Yes	1559	96.7%	98.3%	98.3%	**99.2%**	95.3%

Household income	<=49,999	390	24.2%	13.7%	21.8%	18.6%	**27.8%**
	50,000-99,999	530	32.9%	34.2%	**34.5%**	29.7%	33.8%
	100,000 or over	692	42.9%	**52.1%**	43.7%	51.7%	38.4%
Household size	One member	340	21.1%	7.7%	10.1%	11.3%	**27.7%**
	Two members	637	39.5%	26.5%	**52.1%**	39.9%	39.3%
	Three or more members	637	39.5%	**65.8%**	37.8%	48.8%	33.0%
Presence of children	No	1198	74.3%	42.7%	77.3%	65.6%	**80.9%**
	Yes	414	25.7%	**57.3%**	22.7%	34.4%	19.1%
Housing tenure	Rent or other	571	35.4%	27.4%	32.8%	29.4%	**38.9%**
	Own	1041	64.6%	**72.6%**	67.2%	70.6%	61.1%
Neighborhood type	Urban	532	33.0%	29.9%	26.9%	26.0%	**36.8%**
	Suburban	914	56.7%	**63.2%**	55.5%	63.0%	53.7%
	Rural	166	10.3%	6.8%	**17.6%**	11.0%	9.5%
Work Arrangement before the Pandemic (fall 2019, retrospectively reported in spring 2020) **vs. fall 2023**							
Monthly commuting days			10.0	**13.0**	8.2	11.2	9.4
Monthly remote working days			2.2	**2.8**	2.3	2.1	2.2
COVID Health Concerns (only measured in spring 2020)							
Level of concerns	Not concerned or neutral	123	7.6%	10.3%	**13.4%**	7.3%	6.7%
	Somewhat concerned	442	27.4%	**29.9%**	24.4%	28.9%	26.8%
	Strongly concerned	1048	65.0%	59.8%	62.2%	63.8%	**66.4%**

				Expected Future Changes in Vehicle Count (Fall 2023 to Fall 2026)			
Variables	**Categories**	**n**	**% / mean**	**Increase 126 7.8%**	**Decrease 67 4.2%**	**Replace 529 32.8%**	**No change 890 55.2%**
General Attitudes[1]							
Pro-environment			0.00	0.06	-0.13	**0.20**	-0.12
Pro-driving			0.00	-0.03	**0.11**	-0.03	0.01
Novelty-seeking			0.00	**0.35**	-0.03	0.19	-0.16

Pro-active			0.00	-0.13	0.07	**0.17**	-0.09
Car-captive			0.00	-0.12	0.11	**0.19**	-0.10
Pro-urban			0.00	-0.09	0.01	-0.07	**0.06**
SDE Characteristics							
Age cohort[2,3]	Millennials or younger (after 1980)	397	24.6%	20.9%	**45.2%**	29.9%	25.3%
	Generation X (1965-1980)	478	29.7%	28.3%	**32.5%**	26.9%	31.6%
	Baby Boomers or older (before 1965)	737	45.7%	**50.8%**	22.2%	43.3%	43.1%
Ethnicity[3]	Non-Hispanic/Latino/Spanish origin	1465	90.9%	84.1%	89.6%	90.4%	**92.2%**
	Hispanic/Latino/Spanish origin	147	9.1%	**15.9%**	10.4%	9.6%	7.8%
Race[3]	Non-white	371	23.0%	**36.5%**	13.4%	23.4%	21.6%
	White	1241	77.0%	63.5%	**86.6%**	76.6%	78.4%
Gender[3]	Not-Female	629	39.0%	33.3%	40.3%	**45.0%**	36.1%
	Female	983	61.0%	**66.7%**	59.7%	55.0%	63.9%
Education attainment	Lower than bachelors	492	30.5%	34.1%	20.9%	22.7%	**35.4%**
	Bachelor or higher	1120	69.5%	65.9%	**79.1%**	77.3%	64.6%
Student status	Not a student	1548	96.0%	88.9%	95.5%	**96.8%**	96.6%
	Student	64	4.0%	**11.1%**	4.5%	3.2%	3.4%
Work status	Non-workers	621	38.5%	25.4%	26.9%	31.4%	**45.4%**
	Workers	991	61.5%	**74.6%**	73.1%	68.6%	54.6%
Possess of a driver's license	No	53	3.3%	**7.1%**	3.0%	0.8%	4.4%
	Yes	1559	96.7%	92.9%	97.0%	**99.2%**	95.6%
Household income	<=49,999	343	21.3%	**27.8%**	13.4%	9.8%	**27.8%**
	50,000-99,999	514	31.9%	29.4%	29.9%	**32.5%**	32.1%
	100,000 or over	754	46.8%	42.9%	56.7%	**57.7%**	40.1%
Household size	One member	376	23.3%	12.7%	16.4%	12.5%	**31.7%**
	Two members	679	42.1%	27.0%	**47.8%**	47.6%	40.6%
	Three or more members	558	34.6%	**60.3%**	35.8%	39.9%	27.8%
Presence of children	No	1251	77.6%	49.2%	82.1%	74.3%	**83.3%**
	Yes	361	22.4%	**50.8%**	17.9%	25.7%	16.7%
Housing tenure	Rent or other	482	29.9%	**41.3%**	23.9%	23.3%	32.7%
	Own	1130	70.1%	58.7%	76.1%	**76.7%**	67.3%
Neighborhood type	Urban	508	31.5%	**42.1%**	32.8%	23.4%	34.6%
	Suburban	929	57.6%	45.2%	55.2%	**65.8%**	54.7%

	Rural	176	10.9%	**12.7%**	11.9%	10.8%	10.7%
Work Arrangement before the Pandemic (fall 2019, retrospectively reported in spring 2020) **vs. fall 2023**							
Monthly commuting days			7.9	**10.1**	8.8	9.0	6.8
Monthly remote working days			5.6	7.2	**7.6**	5.6	5.3
COVID Health Concerns (only measured in spring 2020)							
Level of concerns	Not concerned or neutral	---[4]	---	---	---	---	---
	Somewhat concerned	---	---	---	---	---	---
	Strongly concerned	---	---	---	---	---	---

Notes:
[1] Numbers denote the average factor scores by the category of change in vehicle count.
[2] An age cohort refers to a group of individuals who were born around the same time period from a particular population that typically shares certain events and experiences over their life course (Bell, 2019).
[3] Age cohort, ethnicity, race, and gender are considered as static variables which typically remain constant for the same individual over time. The rest of variables are considered as time-varying or dynamic variables.
[4] Cells with "---" indicate variables that are not tested in the model due to lack of information.
[5] Bolded values represent the highest value within each respective row, while values with underscore represent the lowest value within each respective row.

Table 3-2 Past and future changes in vehicle count by life events and changes in work arrangement between two timepoints

				Past Changes in Vehicle Count (spring 2020 to fall 2023)			
Variables	**Categories**	**n**	**% / mean**	**Increased 117 7.3%**	**Decreased 119 7.4%**	**Replaced 381 23.6%**	**No change 995 61.7%**
Life Events and Changes in Work Arrangements							
Changes in education attainment	No change	1510	93.7%	90.6%	**96.6%**	94.5%	93.4%
	Increase	102	6.3%	**9.4%**	3.4%	5.5%	6.6%
Changes in student status	No change	1517	94.1%	90.6%	**95.8%**	92.9%	94.8%
	Student --> Non-student	63	3.9%	**5.1%**	3.4%	5.0%	3.4%
	Non-student --> Student	32	2.0%	**4.3%**	0.8%	2.1%	1.8%
Changes in work status	No change	1340	83.1%	82.9%	**85.7%**	82.2%	83.1%
	Worker --> Non-worker	81	5.0%	3.4%	5.0%	4.7%	**5.2%**

	Non-worker --> Worker	193	12.0%	**13.7%**	<u>9.2%</u>	13.1%	11.7%
Changes in household income	No change	974	60.4%	<u>48.7%</u>	59.7%	57.0%	**63.1%**
	Decrease	189	11.7%	<u>7.7%</u>	**15.1%**	11.0%	12.1%
	Increase	450	27.9%	**43.6%**	25.2%	32.0%	<u>24.8%</u>
Changes in number of children (<18)	No change	1367	84.8%	<u>60.7%</u>	84.0%	81.1%	**89.1%**
	Decrease	156	9.7%	**28.2%**	10.1%	10.5%	<u>7.2%</u>
	Increase	89	5.5%	**11.1%**	5.9%	8.4%	<u>3.6%</u>
Changes in number of adults (18-64)	No change	1096	68.0%	<u>61.5%</u>	68.1%	65.6%	**69.6%**
	Decrease	372	23.1%	<u>15.4%</u>	23.5%	**24.4%**	23.4%
	Increase	143	8.9%	**23.1%**	8.4%	10.0%	<u>6.9%</u>
Changes in number of old adults (65+)	No change	1336	82.9%	**90.6%**	<u>78.2%</u>	85.0%	81.7%
	Decrease	61	3.8%	<u>2.6%</u>	**7.6%**	3.7%	3.5%
	Increase	214	13.3%	<u>6.8%</u>	14.3%	11.3%	**14.8%**
Changes in residential relocation	No	1217	75.5%	<u>67.5%</u>	76.5%	74.5%	**76.7%**
	Yes	395	24.5%	**32.5%**	23.5%	25.5%	<u>23.3%</u>
Changes in level of urbanization	No change	1356	84.1%	82.1%	<u>81.5%</u>	83.5%	**84.9%**
	Decrease	143	8.9%	**13.7%**	10.9%	9.2%	<u>8.0%</u>
	Increase	111	6.9%	<u>4.3%</u>	**7.6%**	7.3%	7.0%
Changes in commuting days			-2.1	-2.5	-3.0	<u>-3.1</u>	**-1.6**
Changes in remote working days			3.4	**5.9**	3.6	4.3	<u>2.7</u>

				Expected Future Changes in Vehicle Count (fall 2023 to fall 2026)			
				Increase	**Decrease**	**Replace**	**No change**
			% /	**126**	**67**	**529**	**890**
Variables	**Categories**	**n**	**mean**	**7.8%**	**4.2%**	**32.8%**	**55.2%**
Life Events and Changes in Work Arrangements							
Changes in education attainment	No change	---[1]	---	---	---	---	---
	Increase	---	---	---	---	---	---
Changes in student status	No change	1570	97.4%	<u>92.9%</u>	**98.5%**	96.8%	98.3%
	Student --> Non-student	18	1.1%	**4.0%**	1.5%	1.3%	<u>0.6%</u>

	Non-student --> Student	24	1.5%	**3.2%**	0.0%	1.9%	1.1%
Changes in work status	No change	1528	94.8%	90.5%	92.5%	95.1%	**95.4%**
	Worker --> Non-worker	31	1.9%	1.6%	**6.0%**	2.5%	1.3%
	Non-worker --> Worker	53	3.3%	**7.9%**	1.5%	2.5%	3.3%
Changes in household income	No change	---	---	---	---	---	---
	Decrease	---	---	---	---	---	---
	Increase	---	---	---	---	---	---
Changes in number of children (<18)	No change	---	---	---	---	---	---
	Decrease	---	---	---	---	---	---
	Increase	---	---	---	---	---	---
Changes in number of adults (18-64)	No change	---	---	---	---	---	---
	Decrease	---	---	---	---	---	---
	Increase	---	---	---	---	---	---
Changes in number of old adults (65+)	No change	---	---	---	---	---	---
	Decrease	---	---	---	---	---	---
	Increase	---	---	---	---	---	---
Changes in residential relocation	No	---	---	---	---	---	---
	Yes	---	---	---	---	---	---
Changes in level of urbanization	No change	---	---	---	---	---	---
	Decrease	---	---	---	---	---	---
	Increase	---	---	---	---	---	---
Changes in commuting days			-0.1	-0.5	-0.8	-0.1	**0.1**
Changes in remote working days			0.03	0.1	0.04	**0.4**	-0.2

Notes:
[1] Cells with “---” indicate variables that are not tested in the model due to lack of information.
[2] Bolded values represent the highest value within each respective row, while values with underscore represent the lowest value within each respective row.

3.4.3 Modeling Approach

In this study, I use an integrated choice and latent variable (ICLV) model to jointly estimate two dependent variables. Each part combines two sub-models: a latent variable model and a discrete choice model (Abou-Zeid & Ben-Akiva, 2014a). The latent variable model addresses the relationships between observable features of the individuals (such as SED and neighborhood characteristics, as well as COVID-19 health concerns) and underlying psychometric factors. The discrete choice model estimates the utility associated with the four types of vehicles count changes, explained by latent attitudes, individual and household characteristics, and life events. Figure 3-4 depicts the modeling framework in this study, and Equations (1) through (4) present the mathematical presentation of the model (Hess et al., 2018).

In the choice model, I estimated two multinomial logit-kernel sub-models (MNL)[5] (Abdulsalam et al., 2013). For each individual n, I considered a set of mutually exclusive discrete alternatives j ($j = 1{:}\,no\ change, 2{:}\,increase, 3{:}\,decrease, and\ 4{:}\,replace$) for choice situation m ($m = 1{:}\,past\ changes, 2{:}\,expected\ future\ changes$). Each individual n is assumed to choose the alternative j that yields the highest utility $\mathrm{u}_{\mathrm{mnj}}$ in each choice situation (as shown in Eq. (4)). Furthermore, the utility is a function of latent variables x_n^*, individuals' observable features s_n at one timepoint and observable changes in features between two timepoints Δs_n (i.e., life events, changes in work arrangements) (as shown in Eq. (1))[6]. In addition, I expect that changes in vehicle count in the past had direct impacts on the expected changes in vehicle count in the future.

---

[5] The MNL model assumes the independence of irrelevant alternatives (IIA) property, which states that the ratio of the choice probabilities between two alternatives is unaffected by the existence or attributes of other alternatives in the choice set (Cheng & Long, 2007; Vijverberg, 2011). To test if IIA holds true, I turn to a nested logit (NL) model, which places similar alternatives within the same nest and distinct alternatives across distinct nests (McFadden, 1978; Williams, 1977). Note that the Lambda parameter, unique to the nest logit, helps determine whether nested structures explain the choice of interest better than non-nested structures, or MNL. I find lambda parameters from the nest logit models is larger than 1, indicating that the nesting structure is invalid and is insistent with the random utility maximization.

[6] For brevity in this explanation and the equations below, the time variable *t* is omitted from the notation. However, when modeling recent and expected changes in vehicle count, individual and household characteristics as well as life events reflect specific timepoints or changes between different time periods.

I estimated two latent variable (LV) models separately for the two MNL models described before. Each LV model consists of two components. The first component is the measurement equations, which estimate the impact of latent variables x_n^* on the attitudinal responses i_n (as shown in Eq. (2)). The initial specifications of these measurement equations were informed by the results of the EFA. Since the psychological constructs of individuals at two timepoints are rather similar, I decided to constrain the matrix of factor loadings D to be the same for the two measurement models. The second component of the LV model contains the structural equations, which define each latent variable x_n^* as a function of individuals' observable features s_n (as shown in Eq. (3)). The model was estimated in R package Apollo (Hess & Palma, 2019) using the Bunch et al. (1993) maximum likelihood estimation algorithm.

Utility specification:

$$\mathrm{u_{mnj}} = \mathrm{B_{mj}}(\mathrm{s_n} + \mathrm{D}\mathrm{s}_n) + \Gamma_{\mathrm{mj}}\mathrm{x}_\mathrm{n}^* + \epsilon_{\mathrm{mnj}}\ ,\ \epsilon_{mnj} \sim i.i.d.Gumbel \quad (1)$$

$\mathrm{u_{mnj}}$: utility of alternative j in choice situation m for individual n; $\mathrm{s_n}$: observable features (e.g., work status) of individual n, reported at one timepoint; Δs_n: observable changes in features (e.g., life events) between two timepoints; $\mathrm{B_{mj}}$: unknown coefficients between each observable feature and each alternative j in choice situation m to be estimated; x_n^*: latent factors of individual n; Γ_{mj}: unknown coefficients between each latent factor and alternative j in choice situation m; ϵ_{mnj}: random disturbances of unobserved component with *i.i.d.* Gumbel distribution.

Measurement equation:

$$\mathrm{i_n} = \mathrm{D}\mathrm{x}_\mathrm{n}^* + \eta_\mathrm{n}\ ,\ \eta_\mathrm{n} \sim N(0, \Psi) \qquad (2)$$

$\mathrm{i_n}$: the level of the agreement to each attitudinal statement of individual n; D: factor loadings indicating the relationship between each indictor and latent factors; η_n: measurement errors with normal distribution $N(0, \Psi)$.

Structural equation:

$$x_n^* = As_n + v_n \text{ , } v_n \sim N(0, \Phi) \qquad (3)$$

A: unknown coefficients between observable features and each latent factor to be estimated; v_n: random disturbances with normal distribution $N(0, \Phi)$; Φ: variance-covariance matrix.

Choice equation:

$$y_{mnj} = \begin{cases} 1, \text{if } u_{mnj} \geq u_{mnj'}, \forall j' \\ 0, \text{otherwise} \end{cases} \qquad (4)$$

y_{mnj} : final choice of individual n among alternative j in choice situation m.

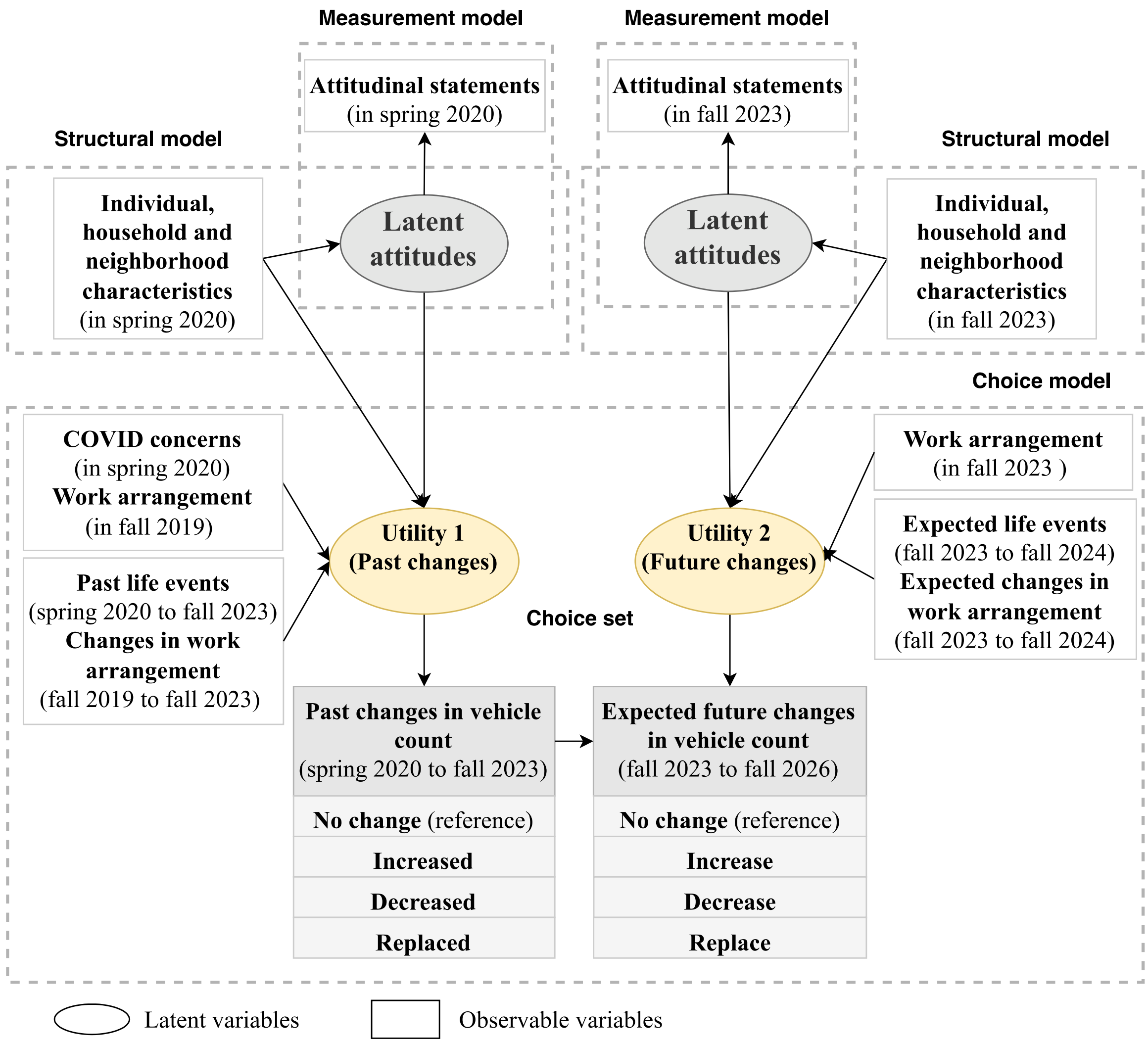

Figure 3-4 Modeling framework of the ICLV model

3.5 Results and Discussions

3.5.1 Results

The measurement model identified four significant latent variables: *pro-environment*, *pro-driving*, *pro-active* and *novelty-seeking*. Table 3-3 displays the coefficients, where higher absolute values indicate a stronger relationship between the latent variables and the respective indicators.

Table 3-3 Results of the measurement model

Latent factors and corresponding attitudinal statements	Coefficient	Robust t-stat[1] and sig.[2]
Pro-environment		
We should raise the cost of driving to provide funding for better public transportation.	1.16	(48.00)***
We should raise the cost of driving to reduce the negative impacts of transportation on the environment.	1.10	(44.29)***
I always think about ways in which I can reduce my impact on the environment.	0.40	(17.03)***
Pro-driving		
I prefer to be a driver rather than a passenger.	0.82	(24.66)***
I like driving a car.	0.80	(20.01)***
I definitely want to own a car.	0.57	(14.31)***
To me, a car is just a way to get from place to place.	-0.49	(-15.14)***
Pro-active		
I like riding a bike.	0.39	(7.88)***
I like walking.	0.36	(7.18)***
Getting regular exercise is very important to me.	0.33	(7.29)***
Novelty-seeking		
I like to be among the first people to have the latest technology.	0.69	(21.40)***
I will stretch my budget to buy something new and exciting.	0.54	(17.42)***
Having Wi-Fi and/or good internet access on my mobile phone. everywhere I go is essential to me.	0.46	(18.31)***
I like trying things that are new and different.	0.34	(13.29)***

Notes:
[1] Robust t-statistic is less sensitive to violations of assumptions than the traditional t-statistic by using methods that are less affected by outliers or non-normality.
[2] Significance level (*10%, **5%, ***1%)

Table 3-4 presents the coefficients of the two structural models. Overall, the level of significance of variables and the magnitude of their impacts are largely consistent across the two timepoints (spring 2020 and fall 2023) for each factor. In both timepoints, the *pro-environment* attitude was stronger among individuals with higher education (Dietz et al., 2002) and urban residents (Ambrosius & Gilderbloom, 2015). Younger cohort is found to be more *pro-environment* in spring 2020 (Yamane & Kaneko, 2021). Females and those with higher education were less *pro-driving*, while those with a driver's license were more *pro-driving*. Housing owners were more *pro-driving* in spring 2020, while suburban or rural residents were more *pro-driving* by fall 2023. As expected, older individuals were less *pro-driving*, likely due to physical limitations. The *pro-active* attitude was stronger among younger individuals and urban residents, as well as those with higher education and incomes at both timepoints (Mondschein, 2021). Additionally, individuals with children and those without a driver's license were more *pro-active* in spring 2020 when kids were mainly do homeschooling and alternative transportation such as walking and cycling become more prevalent (Cusack, 2021), but this trend did not persist into fall 2023. Finally, younger individuals, those of Hispanic origin, individuals with higher household incomes, those with children in the household, and urban residents tend to be more *novelty-seeking*.

Table 3-4 Results of the structural model

Variables	Categories	Pro-environment		Pro-driving		Pro-active		Novelty-seeking	
		Spring 2020	Fall 2023	Spring 2020	Fall 2023	Spring 2020	Fall 2023	Spring 2020	Fall 2023
Age cohort (ref: Millennials or younger)	Generation X	-0.26 (-3.40)***			-0.07 (-0.61)		-0.36 (-2.60)***	-0.20 (-1.96)**	-0.10 (-1.01)
	Baby Boomers or older	-0.21 (-2.67)**			-0.20 (-1.98)**		-0.53 (-3.54)***	-0.60 (-6.15)***	-0.50 (-5.78)***
Gender (ref: non-female)	Female			-0.56 (-6.60)***	-0.63 (-7.39)***				
Ethnicity (ref: non-Hispanic)	Hispanic							0.42 (2.82)***	0.38 (2.80)***
Education attainment (ref: lower than bachelor's degree)	Bachelor's degree or higher	0.63 (9.91)***	0.59 (10.62)***	-0.36 (-4.33)***	-0.56 (-6.93)***	0.61 (4.31)***	0.57 (4.17)***		
Household annual income (ref: less than $50,000)	$50,000 - $99,999					0.31 (1.85)*	0.43 (4.16)***	0.31 (3.20)***	0.22 (2.05)**
	$100,000 or more					0.72 (3.90)***	0.56 (3.90)***	0.52 (5.61)***	0.23 (2.67)***
Presence of children (ref: no)	Yes					0.50 (3.79)***		0.45 (4.47)***	0.35 (3.25)***
Housing Tenure (ref: rent or other)	Own			0.22 (2.54)**					
Neighborhood type (ref: urban)	Suburban	-0.33 (-4.68)***	-0.58 (-9.75)***		0.33 (3.53)**	-0.29 (-2.33)**	-0.40 (-2.90)***	-0.25 (-2.99)***	-0.21 (-2.56)***
	Rural	-0.06 (-0.61)	-0.42 (-4.17)***		0.38 (2.54)**	-0.05 (-0.24)	-0.31 (-1.49)	-0.44 (-3.05)***	-0.52 (-3.90)***
Having a driver's license (ref: no)	Yes			0.45 (4.21)***	0.67 (4.97)***	-0.79 (-4.62)***			

Note: Statistics in the table represent coefficients, robust t-statistics, significance level (*10%, **5%, ***1%).

Table 3-5 reports the results of the two multimodal logit models concurrently modeling past and expected future changes in household vehicle count with “no change” as the reference category. Between spring 2020 and fall 2023, individuals with a stronger *pro-environment* stance were less likely to have replaced vehicles, whereas those with greater proclivity for active lifestyles were more likely to do so. Individuals who are more *pro-driving* are more likely to expect to replace their vehicles in the future. Unsurprisingly, individuals characterized by a propensity for *novelty-seeking* have higher chances of altering their vehicle count. They are more likely to acquire new vehicles, dispose of their current ones, or replace existing one(s) with new vehicles.

Beyond indirect effects (through the latent attitudes), individuals’ SED traits also directly affect changes in vehicle count. Younger generations (Millennials or younger) were more likely to have increased their number of vehicles in the household compared to older cohorts (Boomers or older). This trend is attributed to the dynamic nature of their household compositions, financial situations, lifestyles, and travel needs, all of which collectively contribute to a greater need for additional vehicles to accommodates commuting obligations and household responsibilities. A similar pattern emerges when comparing Millennials to Gen X regarding the expected VO change in the coming three years. Furthermore, females exhibited a lower inclination towards augmenting their vehicle counts. This aligns with existing research highlighting lower car dependence among women compared to men (den Braver et al., 2020; Guan & Wang, 2019). Additionally, within multi-member households, females may exert lesser influence over vehicle ownership decisions, especially if they are not employed. Households with children were more predisposed to have increased or to expect to increase their vehicle count.

I observe a positive correlation between the increase in the number of children/adults and the rise in household vehicles during the pandemic, consistent with prior research (Goodwill, 1993; J. H. Lee & Goulias, 2018; Thakuriah, 2024). Higher educational attainment in fall 2023 is associated with a higher likelihood of vehicle replacement in the subsequent years. In a similar vein, those with higher income levels were more likely to have increased their vehicle count in the past and to expect vehicle replacement in the future (Thakuriah, 2024). Households whose income has increased in the recent past were more likely to have added or replaced a vehicle(s) than those without income changes.

Holding all else constant, larger households tend to decrease or replace their cars compared to single-person households, and white individuals are less inclined to expect an increase in their vehicle counts in the coming years. It is well-established that larger households and white individuals typically already possess sufficient vehicles to meet their travel needs adequately.

Work status also plays a significant role in the changes in vehicle count. Individuals expected to start or resume work by fall 2024 were more likely to increase their vehicle count in the future, while those anticipating a pause or termination in employment were more likely to shed their vehicle(s). Regarding work arrangement, a higher monthly commuting frequency is associated with a decreased likelihood of vehicle reduction in the past, and an increased likelihood of vehicle addition or replacement of their vehicle in the future. Additionally, an increase in commuting frequency between spring 2020 and fall 2023 was negatively associated with vehicle-shedding during those years, while an expected increase in remote working frequency after 2023 is positively associated with plans to replace a vehicle in the future.

Individuals who expressed concerns about the health impact of the pandemic in spring 2020 were less likely to have decreased their vehicle counts during that time. This trend reflects shifts towards private means of travel (e.g., driving) due to lingering health concerns during the pandemic (Loa et al., 2021; Zhang et al., 2021).

Finally, individuals who increased their household vehicle count during the pandemic are more likely to either increase, decrease or replace their vehicle count in the next three years. Those who shed their vehicles are more inclined to acquire vehicles, while those who replaced vehicles are more likely to do so again in the future.

Table 3-5 Results of the choice model

Variables	Categories	Past changes in vehicle count (spring 2020 to fall 2023, "no change" as the reference): Increase	Decrease	Replace	Expected future changes in vehicle count (fall 2023 to fall 2026, "no change" as the reference): Increase	Decrease	Replace
Constants		-2.56 (-9.49)***	-2.11 (-5.23)***	-1.74 (-9.95)***	-1.98 (-6.45)***	-2.76 (-15.04)***	-2.13 (-10.51)***
Attitudes							
Pro-environment				-0.14 (-2.09)**			
Pro-driving							0.24 (3.06)***
Pro-active				0.24 (1.83)*			
Novelty-seeking					0.24 (1.83)*	0.27 (1.76)*	0.22 (3.68)***
Socio-demographics and Neighborhood Characteristics							
Age cohort (ref[1]: Millennials or younger)	Generation X	-0.22 (-0.99)			-0.50 (-2.24)**		
	Baby Boomers or older	-1.25 (-4.17)***			-0.58 (-1.99)**		
Gender (ref: non-female)	Female	-0.43 (-2.09)**					
Race (ref: not white only)	White only				-0.62 (-2.95)***		
Educational attainment (ref: lower than bachelor's degree)	Bachelor's degree or higher						0.36 (2.52)**
Household size (ref: one member)	Two members		1.31 (4.01)***	0.68 (3.50)***			0.63 (3.67)***
	Three or more members		1.26 (3.71)***	1.02 (5.12)***			0.67 (3.65)***
Presence of a child(ren) (ref: no)	Yes	1.07 (4.98)***			1.29 (5.82)***		
Annual household income (ref: less than $50,000)	$50,000 - $99,999	0.39 (1.26)					0.75 (3.91)***
	$100,000 or more	0.91 (2.96)***					0.71 (3.70)***
Work Arrangement before the Pandemic (in 2019, retrospectively reported in spring 2020) vs. fall 2023							
Monthly commute days			-0.04 (-2.96)***		0.02 (1.77)*		0.01 (2.11)**
COVID Health Concerns (only Measured in Spring 2020)							

Variables	Categories	Past changes in vehicle count (spring 2020 to fall 2023, "no change" as the reference)			Expected future changes in vehicle count (fall 2023 to fall 2026, "no change" as the reference)		
		Increase	**Decrease**	**Replace**	**Increase**	**Decrease**	**Replace**
Level of concerns	Somewhat concerned		-0.93		---	---	---
(ref: not concerned or neutral)			(-2.79)***		---	---	---
	Strongly concerned		-0.93		---	---	---
			(-3.09)***		---	---	---
Life Events and Changes in Work Arrangements							
Changes in Employment status	Worker → non-worker				0.24	1.25	
(ref: no change)					(0.32)	(2.20)**	
	Non-worker → worker				1.23	-0.67	
					(3.27)***	(-0.65)	
Changes in Household income	Increased	0.84		0.38	---	---	---
(ref: no change)		(3.75)***		(2.78)***	---	---	---
Changes in Number of kids (<18)	Increased	0.74		0.69	---	---	---
(ref: no change)		(2.05)**		(2.70)***	---	---	---
Changes in Number of adults (18-64)	Increased	0.80		1.05	---	---	---
(ref: no change)		(3.06)***		(3.81)***	---	---	---
Change in commute days	Increased/Expected to increase		-0.04	-0.02			
			(-2.75)***	(-2.51)**			
Change in remote working days	Increased/Expected to increase						0.02
							(2.31)**
Past Household Vehicle Count Changes (from spring 2020 to fall 2023)							
Changes in vehicle count	Increased	---	---	---	1.05	1.39	0.45
(ref: no change)		---	---	---	(3.27)***	(3.87)***	(1.86)*
	Decreased	---	---	---	1.35		
		---	---	---	(4.73)***		
	Replaced	---	---	---			0.69
		---	---	---			(5.24)***
# of Observation		Increase 117; Decrease 119; Replace 381; No change 995			Increase 126; Decrease 67; Replace 529; No change 890		
LL(0)				-2137.67			-2137.67
LL(final model)				-1486.68			-1449.06

Notes:
1. "ref" represents the reference category for a given variable. 2. Statistics in the table represent coefficients, robust t-statistics, and significance level (*10%, **5%, ***1%). 3. Blank cells indicate variables that are tested in the model but not statistically significant, whereas cells with "---" indicate variables that are not tested in the model due to lack of information.

3.5.2 Discussions

The study found that individuals who are *pro-driving* and *novelty-seeking* are more likely to consider increasing or replacing their vehicles in the future. This is consistent with other studies showing that individuals with these attitudes are also more inclined to embrace new vehicle technologies, such as EVs (Iogansen et al., 2023), autonomous vehicles (Wang & Akar, 2019), and shared mobility services, such as ridehailing (Lavieri & Bhat, 2019), carsharing (Mueller et al., 2015) and micromobility (Mahmoud et al., 2021). Policies aimed at incentivizing these individuals to transition to cleaner vehicles or promoting mode shift away from private vehicles altogether, could have significant impacts on reducing carbon emissions.

Younger individuals have higher likelihood in increasing vehicle count compared to their older counterparts, likely due to their more dynamic household composition, financial conditions, and student/work status. It is important to formulate policies that divert younger individuals away from increasing vehicle ownership, especially among those who are currently non-vehicle owners. The presence of children is positively associated with increased vehicle counts, and an increase in the number of kids and adults in the household is linked to an increase in vehicle counts. A deeper understanding of how vehicles are shared and used among household numbers, and how daily trip chaining patterns are structured would be crucial to help policymakers and car manufacturers develop transportation policies and designing vehicles that meet the diverse needs of larger families. Higher educational attainment and income levels are positively associated with vehicle addition and replacement.

In terms of work status, those who expected a transition to employment in the near future also expect to increase their number of vehicles in the household. Commuting is also positively associated with a lower likelihood of shedding vehicles during the pandemic and a higher likelihood of purchasing/replacing vehicles in the future. However, I did not observe significant impacts of remote work on vehicle count in the past. This may indicate that the effect of remote work on vehicle count largely relates to its influence on commute frequency.

While the ICLV model offers valuable insights into the impact of exogenous variables on the outcomes, model coefficients alone may not clearly reflect the magnitude of these effects and their policy implications. Accordingly, I use the Average Treatment Effect (ATE) (Heckman & Vytlacil, 2000) to quantify the impact of specific variables by assessing how the average predicted probability of each outcome changes when a variable transitions from one state to another, while holding all other factors constant. For example, if altering work arrangements (e.g., reducing commute frequency or increasing remote work frequency) is found to reduce vehicle count, then implementing commute trip reduction policies and remote working policies, would lead to a reduction in vehicle ownership. To estimate the ATE of work arrangements, workers are assumed to be in four distinct states (S1- S4) relative to the base state (S0), in term of the level of commuting frequency. Then, using the estimated ICLV model, I can compute the probability of each alternative within the choice set for each state (S0-S4) at the individual level. The ATE is the difference between the average predicted probability for state S1- S4 and S0. The states are defined as follows:

- S0: self-reported commute frequency;
- S1: commute 20 days per month (fully commute, lower bound of commute reduction intervention);
- S2: reduce monthly commute frequency by 25% (weaker intervention);
- S3: reduce monthly commute frequency by 50% (stronger intervention);
- S4: commute 0 days per month (fully remote work, upper bound of intervention).

Table 3-6 presents *changes* in the average predicted probability of past and expected changes in vehicle count (in percentage points or p.p.) using the ATE for commuting frequency. Reducing commute trips during the pandemic led to a greater increase in probability of vehicle-shedding, compared to post-pandemic period (e.g., a 3.16 p.p. increase for individuals with zero commutes for vehicle count change in the past versus a 0.31 p.p. increase for vehicle count change in the future). Not surprisingly, the effect is larger during the pandemic period, at a time in which travel was largely restricted: A lower number of commuting trips would lead to household vehicles being used less, thereby encouraging vehicle shedding. In contrast, by fall 2023, the demand for non-commuting trips had largely rebounded. Even if workers reduced their number of commute trips, household vehicles would be still likely needed for other purposes, reducing the probability of vehicle shedding. Nevertheless, it is still expected that reducing commute trips will decrease the likelihood of increasing household vehicles in the future (e.g., a 1.11 p.p. decrease for individuals with zero commutes).

Table 3-6 Average treatment effect of work arrangements (in percentage points)

State	Interventions in work arrangement status	Past changes (among those who were workers in spring 2020 and fall 2023, n=799)			
		Increase	Decease	Replace	No change
S1	Fully commute (commute 20 days/month)	0.43	-1.70	-1.04	2.30
S2	Reducing a quarter of current commute freque	0.00	0.63	-0.47	-0.15
S3	Reducing half of current commute frequency	-0.02	1.35	-0.96	-0.38
S4	No commute (commute 0 days/month)	-0.09	3.16	-1.98	-1.09

State	Interventions in work arrangement status	Expected changes (among those who were workers in fall 2023 and expected to be workers in fall 2024, n=799)			
		Increase	Decease	Replace	No change
S1	Fully commute (commute 20 days/month)	0.70	-0.21	1.78	-2.27
S2	Reducing a quarter of current commute freque	-0.29	0.08	-0.64	0.85
S3	Reducing half of current commute frequency	-0.57	0.16	-1.29	1.71
S4	No commute (commute 0 days/month)	-1.11	0.31	-2.59	3.39

Notes:

- State S1 to S4 were established by updating the values in two variables, "monthly commute days" and "change in monthly commute days".
- Respondents who already commute more than 20 days/month maintain their current commute frequency in the S1 state.
- The values in the table are changes in the average predicted probability of past and expected changes in vehicle count (in percentage points).

If governments have the goal of promoting reduction in vehicle ownership (and use), they should support companies in formulating polices designed to reduce commute trips and effectively manage remote and hybrid work arrangements. However, the impact of such policies can vary depending on the level of flexibility offered. For instance, partial-day hybrid work seems to offset the trip reduction benefit from full-day remote working. Policies also need to be customized for different population segments: Individuals who have the option to work remotely entirely will likely reduce the number of vehicles they own. However, those who still need to commute might still need good access to vehicles to access jobs and opportunities.

The study sheds light on the relationship relating certain variables and *changes* in vehicle counts, which may not necessarily translate into impacts of the same variables on vehicle ownership (and counts). Essentially, vehicle count and changes in vehicle count are two interrelated choices which may be driven by different decision-making processes. For instance, this study found that being *pro-driving* did not directly influence the changes in vehicle count during the pandemic, while a relationship between *pro-driving* and the overall vehicle ownership and usage is expected (and is well established in the scientific literature).

Finally, consistent with Kitamura & Bunch (1990), the findings reveal a noticeable behavioral asymmetry regarding specific factors. For instance, an increase in income and the number of adults and children in the household is associated with a significantly higher likelihood of vehicle augmentation or replacement. Conversely, a decrease in income and the number of adults and children does not appear to have a corresponding effect on reducing vehicle counts, once household habits for car use have been established.

3.6 Conclusions

Using a panel dataset comprising respondents from 1,612 U.S. residents, this study explores the factors influencing changes in vehicle count retrospectively between spring 2020 and fall 2023 and prospectively between fall 2023 and fall 2026. I estimated an ICLV model that jointly estimates two multinomial logit models to explain these changes, with latent attitudes, SED characteristics, life events, work arrangements and COVID-related health concerns as explanatory variables. The results indicate that *pro-driving, pro-environment, and pro-active* individuals were more prone to replacing their vehicles, while *novelty-seeking* individuals exhibited a higher propensity to increase, decrease and replace their vehicles. Moreover, younger individuals, households with children, and those experiencing an increase in the number of children or adults within their households had a higher likelihood of acquiring vehicles, likely to accommodate their dynamic travel needs. Transitions into the workforce and an increase in household income during the study period were associated with an increased likelihood of vehicle acquisition. Furthermore, an increase in commute frequency was associated with a lower likelihood of vehicle shedding in the past, and increased likelihood of vehicle purchasing in the future. Not surprisingly, COVID health concerns led to a decreased likelihood of vehicle shedding during the pandemic. Finally, households that increased vehicle count during the pandemic are likely to adjust it again, while those who shed vehicles tend to reacquire them, and those who replaced vehicles are inclined to do so again. Policymakers can leverage the findings on the impacts of latent attitudes, SED characteristics and life events on vehicle count changes to cater to individuals and households with diverse socioeconomic backgrounds. Employers could refine their remote and hybrid work policies to effectively reduce commute trips and vehicle counts.

This study presents several limitations. Survey respondents were asked to report only one type of change by comparing vehicle counts at specific timepoints. However, respondents may have experienced or expected “multiple” changes between these time points. For instance, an individual may have replaced one vehicle and subsequently shed another. Unfortunately, in a case like this, the survey data only capture the behavior of vehicle shedding, neglecting the vehicle replacement. Using mutually exclusive choices, such as replacement, disposal without replacement and acquisition without disposal used by Yamamoto (2008), can resolve this issue. Furthermore, the choice outcomes provided by respondents solely indicate the direction of change in vehicle count, rather than the magnitude: If a respondent reported a decrease in their household vehicle count, I cannot discern whether vehicle count decreases by one vehicle or more. Moreover, despite testing a wide range of model specifications, certain key household-level attributes cannot be controlled in the study. Vehicle ownership tend to be a household decision (Woldeamanuel et al., 2009). For example, fluctuations in the number of household workers could impact on the changes in vehicle counts, but this information was not collected in the survey.

I propose several avenues for future research. First, given the rapid evolution of the auto industry and surge in vehicle transactions as the economy recovered, continued efforts to study this topic could yield major insights in the years ahead. This study can be expanded by investigating vehicle fleet composition and fuel type choices. Research questions related to which vehicles are the first to be discarded during income declines, or whether compact cars are replaced with larger crossovers or SUVs in response to increased household size are worthy of investigation. The data available for this study include details of all passenger vehicles available to the households (including make, model, year, and fuel type) in spring 2020 and fall 2023. Leveraging this information could provide insights into whether individuals upgraded or downgraded, upsized, or downsized their vehicles. Third, the model did not detect the influence of neighborhood characteristics on changes in vehicle count. Introducing location-based variables into the analysis may provide greater insights, when studying, for example, transit-rich vs. transit-poor neighborhoods/cities. Further exploration of this phenomenon can shed more light on the interplay between neighborhood characteristics and vehicle ownership dynamics. Finally, the analysis falls short in distinguishing causation from correlation, a focus that could be explored in further research.

Acknowledgments

Funding to support this research was primarily provided through a combination of grants from the California Air Resources Board (CARB) [award number: 19STC006], the University of California Institute of Transportation Studies Statewide Transportation Research Program funded by State of California (SRTP/SB1), and the Southern California Association of Governments (SCAG) [award number: 21-024-C01]. Additional funding was provided by the California Department of Transportation (Caltrans) [award number: 65A0686] and the 3 Revolutions Future Mobility (3RFM) Program of the University of California, Davis. Special thanks to Yongsung Lee, Jai K Malik, and Giovanni Circella for their invaluable contributions as coauthors of this study. The authors would also like to thank many colleagues that contributed to the survey design, data collection for this project, including Susan Handy, Patricia Mokhtarian, David Bunch, Dillon Fitch, Grant Matson, Basar Ozbilen, Siddhartha Gulhare, Keita

Makino, Marcus Chan, Nicholas Johnson, Sean McElroy, Junia Compostella, Kailai Wang, Maha Ahmad, Maria Carolina Lecompte, Mischa Young, Rosa Dominguez-Faus, Jaime Soza-Parra and Tho V Le.

4 Ridehailing Use, Travel Patterns, and Multimodality: A Latent-class Cluster Analysis of One-week GPS-based Travel Diaries in California[7]

4.1 Abstract

Based on the analysis of one-week GPS-based travel diary data from the four largest metropolitan areas in California, this study performs a latent class cluster analysis and identifies four distinctive traveler groups with varying levels of multimodality. These groups are characterized by their distinctive use of five travel modes (i.e., single-occupant vehicles, carpooling, public transit, biking, and walking) for both work and non-work trips. Two of these groups are more car-oriented and less multimodal (i.e., Drive-alone Users and Carpoolers), whereas the other two are less car-oriented and display higher levels of multimodality (i.e., Transit Users and Cyclists). Results from this study reveal the unique profiles of each traveler group in terms of their sociodemographic characteristics and built-environment attributes. The study further investigates the distinctive characteristics of each traveler group in relation to ridehailing adoption, trip frequency and trip attributes. Transit users are found to have the highest rate of ridehailing adoption and usage. They are also more prone to use pooled ridehailing services in comparison to other groups. In terms of mode substitution, if ridehailing were not available, respondents tend to choose the mode they use most frequently. In other words, car-based travelers are more likely to substitute ridehailing trips with car trips, whereas non-car-based travelers are more likely to replace ridehailing with less-polluting modes. The findings from this study will prove valuable for transit agencies and policymakers interested in integrating ridehailing with other modes and promoting more multimodal and less car-dependent lifestyles.

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[7] This chapter is a short version of a journal paper (Iogansen et al., 2025): *Iogansen, X., Lee, Y., Young, M., Compostella, J., Circella, G., & Jenn, A. (2025). Ridehailing use, travel patterns and multimodality: A latent-class cluster analysis of one-week GPS-based travel diaries in California. Travel Behaviour and Society, 38, 100855. https://doi.org/10.1016/j.tbs.2024.100855.*

4.2 Introduction

Cities have been actively seeking ways to reduce reliance on automobiles (Geels, 2012; Spickermann et al., 2014) and promoting multimodality - the use of multiple means of travel for a given period - has been recognized as a possible pathway to support sustainable mobility (Banister, 2008; Kuhnimhof et al., 2006; Nobis, 2007). In recent years, the emergence of information and communication technologies (ICTs) has facilitated easier connection between traditional modes of transportation (such as private vehicles, buses, and trains) and a wide range of new mobility services (such as carsharing, ridehailing, and bikesharing).

Recent research has extensively examined the impact of ridehailing services, offered by TNCs such as Uber and Lyft, on mobility and travel patterns, but the findings remain inconclusive. One strand of literature suggests that ridehailing can bridge travel gaps for non-vehicle households or those previously excluded by the taxi industry (Brown, 2019; Circella et al., 2018; X. Wu & MacKenzie, 2021), substitute for private vehicles (Henao & Marshall, 2018; Z. Zou & Cirillo, 2021), and complement public and active transportation (Conway et al., 2018; Feigon & Murphy, 2018; J. D. Hall et al., 2018; Sikder, 2019). On the contrary, other studies suggest that ridehailing has increased VMT, road congestion and GHG emissions (Erhardt et al., 2019; Henao & Marshall, 2018; X. Wu & MacKenzie, 2021) while driving down the ridership of public transit (Diao et al., 2021; Hall et al., 2018; Tang et al., 2019). There are also studies that suggest both the complementary and substitution effects of ridehailing on various modes coexist (Circella & Alemi, 2018; Rayle et al., 2016; Shaheen, 2016; Young et al., 2020). For instance, Chen et al. (2021) found that ridesplitting reduces the usage of taxis and private cars but attracts passengers from non-passenger/private vehicles (e.g., bus and metro transit).

Previous studies have typically relied on conventional questionnaire surveys to investigate ridehailing trips on a *one-off* basis, often asking respondents to recall and self-report information about their most recent ridehailing trip (Circella & Alemi, 2018) or their use of ridehailing during a single day of travel (X. Wu & MacKenzie, 2022). However, this approach is not only prone to recall errors and biases (Stopher, 1992), but also overlooks the “inertia effects” of travel decisions, the latent tendency of using (or not using) certain means of travel on a *regular* basis (Vij et al., 2013). A more accurate and comprehensive representation of individuals' modality styles requires multi-day observations to capture both the variability and the stability of their travel behavior (Buehler & Hamre, 2015; Kuhnimhof et al., 2006; Nobis, 2007). To overcome the data challenges, many studies have emphasized the benefit of using Global Positioning Systems (GPS) technology in conjunction with traditional questionnaire methods (Bohte & Maat, 2009; Y. Lee et al., 2022; Tsui & Shalaby, 2006; Wolf et al., 2003). This combined approach has several advantages, including the ability to gather more accurate and objective data on the spatial and temporal aspects of travel and to reduce the measurement errors inherent in self-reported data. There are a few studies on ridehailing, though not conducted in the US context, that have utilized multi-day passively collected GPS trajectory data to capture ridehailing trips, but researchers were either could not link trip data with rider profiles to conduct individual-level analyses (Li et al., 2019) or were unable to incorporate ridehailing into multimodality analyses more broadly (Chen et al., 2021).

This study aims to fill in those gaps by investigating the interrelationships among ridehailing use, travel patterns and multimodality using a week-long (consecutively observed) GPS-based trip diary dataset collected from four metropolitan regions in the State of California during 2018 and 2019. The data incorporates both passively collected GPS tracking data and actively collected questionnaires, which are expected to capture more comprehensive mobility patterns of individuals, with reduced biases or errors associated with recall-based surveys. The study consists two objectives: (1) using a latent class cluster analysis (LCCA), I will identify distinctive traveler groups with unique trip profiles (i.e., weekly trip frequency by modes) and personal characteristics within a sample of 5,053 commuters; (2) I will then investigate the *association* between multimodality and ridehailing adoption/usage and examine ridehailing trip attributes (e.g., when, where, and for what purpose) for traveler groups with distinctive forms of multimodality.

The remainder of this chapter is organized as follows. Section 4.3 review the literature on ridehailing within the context of modality research. Section 4.4 describes the data and methodology.

Section 4.5 presents main findings, discussions, and key contributions. Lastly, Section 4.6 concludes the study with suggestions for future research.

4.3 Literature Review

Investigating day-to-day behaviors is crucial to capture the stability and variability of a person's modality. Some studies rely on multi-week consecutive observations or longitudinal data collection at several time points. While these studies offer better-quality data to explore the rhythm and long-run dynamics of travel behavior, they are often constrained by high survey administration costs and low retention rates, leading to smaller sample sizes and potential biases. Examples include the Mobi*drive* project, which conducted a six-week continuous travel diary survey in two German cities (Axhausen et al., 2002), the Netherlands Mobility Panel study, which conducted a three-day travel diary repeatedly among the same participants over five years (Hoogendoorn-Lanser et al., 2015), and the Puget Sound Transportation Panel Survey (Puget Sound Regional Council, 2002). To balance the data quality and cost concerns, some studies suggest that a one-week consecutive observation is sufficient (Buehler & Hamre, 2015; Kuhnimhof et al., 2006; Nobis, 2007). For example, Pas (1988) used weekly travel-activity patterns to describe respondents' travel-related lifestyles, and Nobis (2007) defined "multimodality" as the use of at least two distinct travel modes within a week. In this study, I will utilize one-week consecutively observed trip data as indicators of modality. I will further discuss the nature of the data in the following section.

Methodologically, previous studies have employed various clustering methods to uncover distinctive travel groups and explore the underlying process that drives individuals' mobility styles. Deterministic classifications have been commonly used. For instance, Buehler & Hamre's study (2015) identified three traveler groups based on a single day's modal decisions from the 2001 and 2009 US National Household Travel Survey data: *monomodal car users*, *multimodal car users*, and *multimodal non-car users*. Their logistic model revealed a continuum of mobility type ranges among these groups. In another study, Diana & Mokhtarian (2009) used self-reported data on the total number of monthly trips taken by different modes to identify four groups of users: *unimodal car users*, *car-dominated but* *multimodal users*, *highly multimodal users with moderate travel intensity*, and *highly multimodal users with heavy travel intensity*. However, they identified four distinct groups based on the total estimated weekly hours spent in those modes: *unimodal car users*, and three car dominated but multimodal traveler groups, but with light/moderate/heavy travel intensity, respectively.

Compared to deterministic clustering, which assign individuals to groups based on predetermined rules, latent class analysis (LCA) has become a more popular technique which uses statistical criteria to determine the optimal number of classes (instead of arbitrarily) and probabilistically assigns individuals to unobserved latent classes (Vermunt & Magidson, 2002). For example, Krueger et al. (2018) used a latent class and latent variable model to examine mobility patterns in Sydney, Australia and identified three classes: *car-oriented users*, *public transport-oriented users*, and *car- and bicycle-oriented users*. In another study, Molin et al. (2016) used latent-class cluster analysis to analyze data from the Netherlands and identified five clusters: *car multimodal*, *bicycle multimodal*, *bicycle and car*, *car mostly*, and *public transport multimodal*. Their classes were mostly built on car and bicycle use since they did not incorporate walking as a separate mode. They estimated the probability of individuals belonging to each of these five identified travel groups based on a function of attitudinal and conventional variables. Using the same approach, Ton et al. (2020) identified five classes of mobility patterns from the 2016 Netherlands Mobility Panel data: *car and bicycle users*, *exclusive car users*, *car/walk/bicycle users*, *public transport users*, and *exclusive bicycle users*. Additionally, De Haas et al. (2018) applied a latent transition model to the same dataset to not only identify six different travel patterns (*strict car, car and bicycle*, *bicycle*, *car and walk*, *low mobility*, and *public transport users*) but also analyze transitions between these patterns over time. In the context of the US, Lee et al. (2020) examined various types of multimodalities among Californian commuters based on user frequency of various modes for both work-related and non-work-related trips. They identified four travel groups, including *monomodal drivers*, *carpoolers*, *active travelers*, and *transit riders*. They also found that economic factors, living arrangements, attitudes/preferences, and related land use attributes all affect an individual's tendency towards travel multimodality.

The aforementioned studies have demonstrated that different mobility groups tend to differ in their attitudes towards auto use, sociodemographic characteristics, the use of different travel modes and built environments. However, these studies typically focused only on traditional modes and often omit or underreport "walking", a common issue in studies based on traditional travel diaries (Handy et al., 2002). Additionally, emerging travel modes, such as ridehailing, have not been widely incorporated in multimodality analyses due to their relative novelty or are often classified as private vehicles during the analyses. Some existing studies suggest that ridehailing is most likely used by multimodalists. Alemi & Circella (2019)'s latent-class model identified three latent classes, finding that *multimodal drivers* who use a variety of transportation modes have the highest average frequency of ridehailing usage (although driving remains their primary mode). Unsurprisingly, *multimodal no car users* also have a high frequency of ridehailing use, while the latent class of *drivers* has the lowest. However, studies also suggest that ridehailing reduces the multimodality of their adopters. Lee et al. (2022) conducted a latent class cluster analysis and revealed four latent classes of changes in mode use as a result of ridehailing adoption. They found that *private car/taxi substituters* use ridehailing frequently, leading to a reduction in trips by private vehicles while increasing trips by public transit and active modes. *Transit/active mode substituters,* initially multimodal travelers prior to the adoption of ridehailing, become less so after substituting public transit, biking, and walking with ridehailing. These mixed findings highlight the need for further examination of this topic. The present study aims to address this gap by disentangling the relationship among ridehailing use, travel patterns and multimodality using a latent class cluster analysis.

4.4 Data and Method

4.4.1 Surveys

The data used in this study was aggregated from two surveys. One is the 2018 Sacramento Regional Transportation Study, administered by the Sacramento Area Council of Governments (SACOG) in six counties from April to May 2018, aimed to understand how people get around daily. The other is the 2018–2019 California TNC User Survey, conducted between November 2018 and November 2019, to support analysis of key policy and planning questions related to TNCs. This survey was a consolidated study among the Metropolitan Transportation Commission (MTC), San Francisco County Transportation Authority (SFCTA), San Diego Association of Governments (SANDAG), and Southern California Association of Governments (SCAG). For more details on the survey's design and implementation, see Bradley et al. (2022). Despite some distinctions between these two datasets, they share many similarities in sampling strategy, data collection methods, contents of the questionnaire, and data weighting strategy which make them compatible for this study's purpose. Further discussions on this topic can be found in the full version of the journal paper (Iogansen et al., 2025).

The combined data from these two surveys is unique for the following reasons. First, it includes observations from four regions (two in Northern California and two in Southern California), the most populated areas in California where most ridehailing drivers and riders are located. This presents a great opportunity to compare findings related to the ridehailing services across the state and explore the inter-individual variations in modal decisions and their determinants. Second, it includes one consecutive week of observations per individual, making the data more reflective of intraindividual variations. In addition, trip information derived from the smartphone GPS tracking app, supplemented by self-reported travel diaries, is believed to be more accurate than traditional surveys, especially for short-distance walking trips. Finally, it contains some unique trip information for each ridehailing trip including trip occupancy, trip cost, mode replacement and so forth.

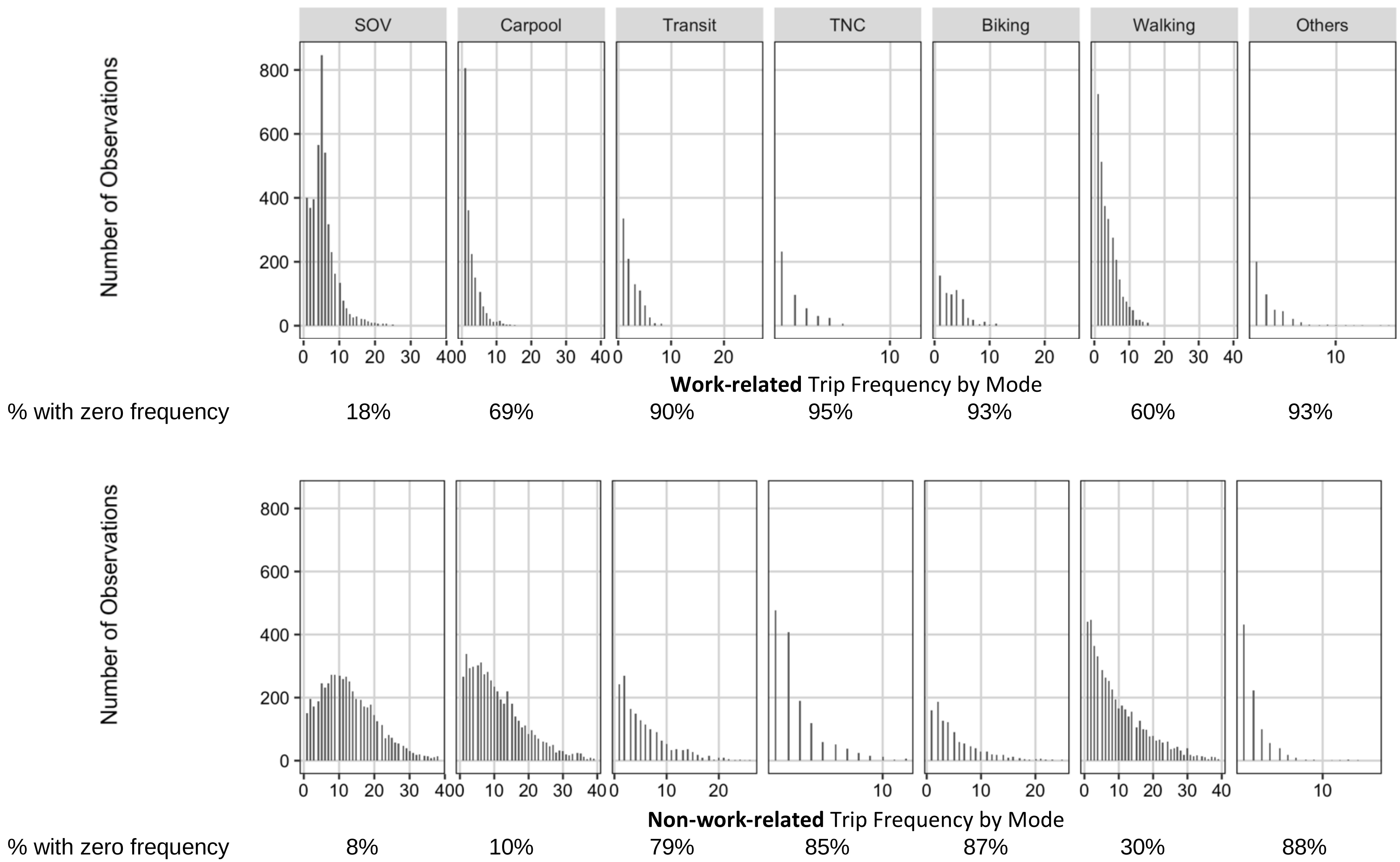
4.4.2 Data Processing and Descriptive Analyses

I processed the data with the following steps. Firstly, the two datasets were merged into one. This study only included individuals with seven consecutive days of complete observations. This criterion ensured a combination of weekdays and weekends, which I considered necessary for analyzing individuals' work and non-work trips. Although this filtering approach excluded a considerable number of respondents, 8,721 respondents (and 368,912 trips) remained, which was deemed an adequate sample size for conducting statistical analyses. Moreover, this study focused exclusively on individuals whose work location differed from their home location. This decision was based on the fact that commuters and non-commuters (e.g., retirees) exhibited distinct activity-travel patterns, as demonstrated in previous studies (Bhat & Singh, 2000; Misra & Bhat, 2000). By excluding non-commuters, I aimed to prevent potential misclassification issues that could arise during the cluster analysis. Additionally, it is worth noting that due to the nature of the pre-pandemic survey, the number of full-time remote workers in the sample was quite limited. Therefore, excluding them did not impact the overall sample size. Lastly, to avoid outliers related to individuals with a large number of trips, I excluded individuals whose primary job involves driving or traveling for work (e.g., Uber/Lyft drivers, truck drivers, food delivery drivers).

Three potential indicators were proposed in the existing literature to delineate daily mobility patterns *(de Haas et al., 2018)*: *distance traveled per mode*, *travel time per mode*, and *the number of trips per mode*. Notably, the number of trips per mode was identified as the most reliable indicator in self-reported studies. Therefore, in this research, I employed *the average frequency of weekly trips per travel mode*, *categorized by travel purposes (*i.e., *work* vs. *non-work)*, to capture both the composition of the travel mode and the level of travel intensity. The trips were classified into the following seven travel mode categories (derived from consolidating 54 detailed modes reported in the original survey): single occupancy vehicle (SOV), carpool, transit, TNC, biking, walking, and all other miscellaneous modes. The "SOV and carpool trips" category includes trips made by vehicles (excluding ridehailing) with one or multiple riders, respectively. When calculating occupancy, both drivers and passengers were included for private-vehicle trips, whereas only passengers were counted for commercial-vehicle trips (e.g., a taxi driver was excluded from the occupancy count). "Public transit trips" includes trips made by heavy rail and all forms of urban mass transit (e.g., buses and trams). The "TNC trips" category encompasses trips made by ridehailing, regardless of whether passengers shared the ride with others or not. "Biking trips" include both traditional bike/ scooter trips and those made using commercial bike-sharing/scooter-sharing services. “Walking trips” encompass walking, jogging, or rolling with a mobility device. Uncommon travel modes such as airplanes or helicopters were assigned to the “Others” category. In terms of trip purposes, any trip that ended with activities related to school, work or work-related tasks was categorized as a *work* trip, while all other trips were categorized as *non-work* trips. This definition aligns with previous studies *(Malik et al., 2021)*.

Figure 4-1 illustrates the histogram displaying one-week trips, categorized by travel modes and trip purposes. The distribution of the data is noticeably skewed and does not conform to a normal distribution. I identified that the data represents count variables with the following characteristics: discrete, non-negative, overdispersed (i.e., the variance exceeds the mean), and with excessive zeros. However, auto-based modes (including SOV and carpooling) have lower proportions of zero values, suggesting their predominant usage for both work and non-work trips. As mentioned, utilization of GPS tracking apps for data collection allows for the observation of a substantial number of walking trips.

Finally, the travel diary data mentioned above was integrated with personal attributes, including individual demographics, household socio-economic status, associated built environments, and other relevant characteristics (refer to Table 4-3 in Section 4.5 for detailed information). After excluding cases with missing information, the final dataset comprises 205,722 trips (accounting for 40.0% of the entire sample), conducted by 5,053 individuals (representing 19.6% of the entire sample).



Note: For better visualization, I have modified the scale of the x-axis for each column and have removed zero frequency observations. The percentage of observations with zero frequency is listed below each plot.

Figure 4-1 Weighted distribution of trips conducted during one week by modes and by trip purposes (n=5,053)

4.4.3 Modeling Approach

Latent-class analysis is widely used in transportation research to identify distinctive traveler groups (de Haas et al., 2018; Molin et al., 2016; Ton et al., 2020). In this study, I employ a LCCA with zero-inflated negative binomial model to investigate the relationship between individuals' modality and their use of ridehailing, and to further explore the potential environmental impacts associated with these choices. LCCA assumes that a given sample comprises multiple latent classes, each possessing unique characteristics. Importantly, researchers do not have prior knowledge of the class to which individual cases belong. Instead, LCCA estimates the probabilities of individual cases belonging to each class, thereby avoiding deterministic class assignments (Buehler & Hamre, 2015). In addition, unlike random-parameter models (e.g., mixed logit), which require a priori distributions for parameter estimates, LCCA models heterogeneity without making strong assumptions (Vermunt & Magidson, 2002). In LCCA, two sub-models are simultaneously estimated. Firstly, the measurement model determines parameter estimates for the class-specific distribution of selected indicators, enabling the identification of diverse forms of heterogeneity within the sample. Secondly, the structural model establishes the relationships between individuals' attributes (referred to as active covariates) and their probabilities of belonging to specific classes.

Figure 4-2 illustrates the implementation of LCCA. I used weekly trip counts by five means of travel (i.e., SOV, carpool, transit, biking, and walking), separately for both work and non-work purposes, as indicators. Note that I excluded "TNC" from this initial step, but rather, I examined and compared (across classes) the characteristics of ridehailing trips in greater detail once the latent classes have been identified. That is, these ridehailing trip attributes were considered as "inactive" covariates. "Active" covariates, which were incorporated into the structural model, include socioeconomic factors, demographic characteristics, transportation subsidies, and land-use attributes.

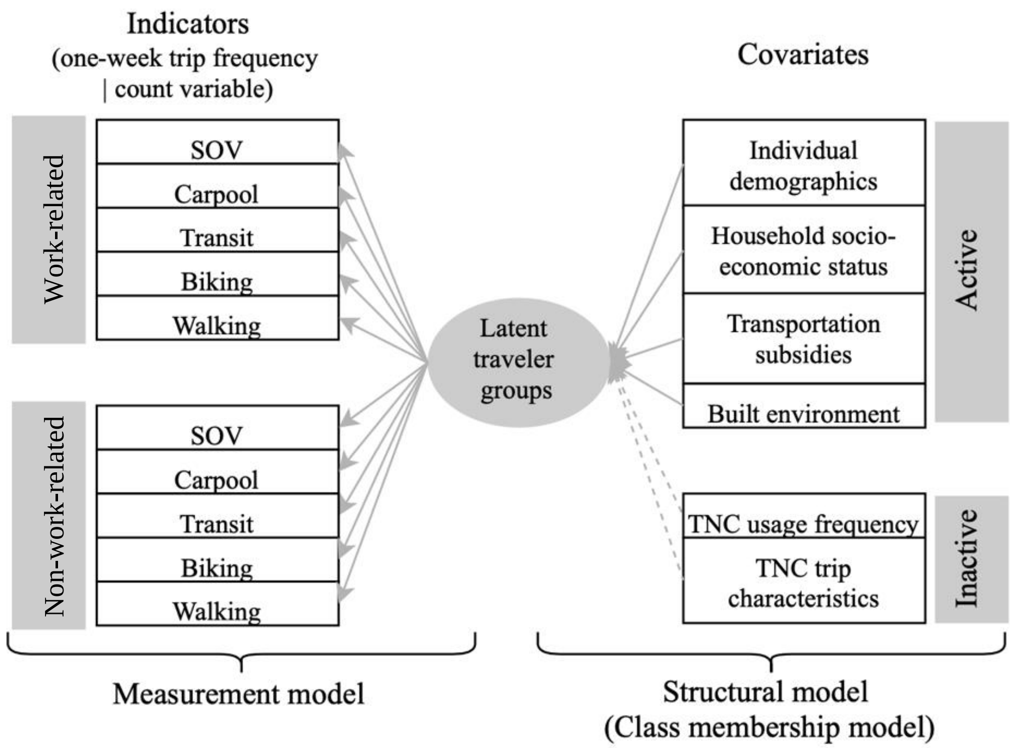


Figure 4-2 Model framework of the latent-class cluster analysis with covariates

To my best knowledge, this study is the first to incorporate trip frequency as count variables within the framework of LCCA, which offers a more realistic and accurate representation of trip data than previous studies that treated trips as continuous variables (Lee et al., 2020). When modeling count variables clustered toward lower values, Poisson regression is most often used, assuming the mean and variance of the variable are equal. However, if the variance exceeds the mean (overdispersion), the negative binomial (NB) model is a more appropriate alternative, which incorporates an extra term to account for the excess variance. In cases where there are an excessive number of zeros, zero-inflated models can also be employed to model excess zeros separately from the count values (Gardner et al., 1995). Given that the trip data exhibits both overdispersion and excessive zeros, the most suitable statistical model for the analysis is the zero-inflated negative binomial (ZINB) model. Some recent studies have also used a ZINB framework to model hourly bike-sharing trips at each station which included many zeros (Hua et al., 2023), daily freight trips within each Traffic Analysis Zone which has a significant percentage of zero trips (Middela & Ramadurai, 2021), and parking violations with excess zero counts on street segments (Hagen et al., 2023).

The following explains the mathematical formulation of LCCA in this study. The ZINB model (i.e., the measurement model) consists of two parts, a logistic regression that predicts the probability of "structural zeros" (i.e., non-users of a particular mode of travel), and a negative binomial model that predicts non-negative counts, which include "sampling zeros" (i.e., users who happened not to use the specified mode of travel during the survey period). Modeling "sampling zeros" overcomes the potential shortcoming of sampling error. Even though these two types of zeros (i.e., non-users and users with zero trips) look identical, they have arrived at the same outcome through two different processes. That is, the number of zeros in the sample is underestimated if modeled only with the second process, so I need to use both processes to accurately estimate both zeros and non-zeros in the sample. In general, for individual *i*, I assume that the first process takes place with probability φ_{ij}, and the second process occurs with probability $1-\varphi_{ij}$.

$$y_{ij} \sim \begin{cases} 0, \quad with\ probability\ \varphi_{ij} \\ g(y_{ij}|x_{ij}), with\ probability\ 1-\varphi_{ij} \end{cases} \tag{1}$$

If the probability φ_{ij} depends on the characteristics of individual *i*, then φ_{ij} is a function of $\beta_j z_{ij}$ (which is a scalar), where z_{ij} is the zero-inflated covariates and β_j is the zero-inflated coefficients to be estimated (Erdman D, Jackson L, 2008). Then the probability of $\{ Y_{ij} = y_{ij} \mid x_{ij}, z_{ij}\}$ is

$$P_{ij}(Y_{ij} = y_{ij}|x_{ij}, z_{ij}) = \begin{cases} \varphi(\beta_j z_{ij}) + \{1-\varphi(\beta_j z_{ij})\}\, g(0|x_{ij}), \ if y_{ij} = 0 \\ \{1-\varphi(\beta_j z_{ij})\}\, g(y_{ij}|x_{ij}), \qquad if y_{ij} > 0 \end{cases} \tag{2}$$

where z_{ij} denotes the covariates. The function that relates the $\beta_j z_{ij}$ to the probability φ_{ij} is called the zero-inflated link function, which is a logistic function in this study. The probability of $\{y_{ij} = 0\}$ versus $\{y_{ij} > 0\}$ is:

$$\varphi(\beta_j z_{ij}) \sim p_{ij}(y_{ij} = 0) = \frac{1}{1 + e^{-\beta_j z_{ij}}} \tag{3}$$

For the second process, the negative binomial model is estimated with the parameter λ_{ij} as the mean of each indicator j for individual i:

$$g(y_{ij}|x_{ij}) \sim p_{ij}\ (y_{ij} \geq 0\ |\lambda_{ij}\ ) = \frac{\theta_j^{\theta_j}\ \lambda_{ij}^{y_{ij}}\ \Gamma(\theta_j + y_{ij})}{\Gamma(y_{ij}+1)\ \Gamma(\theta_j)\ (\lambda_{ij}+\theta_j)^{\theta_j + y_{ij}}} \tag{4}$$

where $1/\theta$ denotes the variance of the unobserved heterogeneity term in negative binomial model to account for overdispersion. As the $1/\theta$ converges to 0, the negative binomial distribution converges to a Poisson distribution. The software *Mplus v.8.6.* which I used for the estimation outputs $1/\theta$ as the dispersion parameter, thus a value statistically significantly different from 0 suggests that estimating a negative binomial model does outperform a Poisson model (Muthén & Muthén, 2017).

With s latent classes in the sample, each having class-specific parameter estimates for β, λ, and θ, the entire model can be described as follows, where m_i represents covariates for the membership model. The entire LCCA model can be described as follows:

$$P(y_i|z, x_i, m_i) = \sum_{s=1}^{S} P(s|m_i) \prod_{j=1}^{10} P(y_{ij}|s) \tag{6}$$

The first part of the model indicates that each individual i has a certain probability of belonging to each latent class s given their covariates m_i. This sub-model estimates a multinomial logit model. The second part of the equation indicates the probability density of individual i's response to indicator j (Y. Lee et al., 2022).

Another important consideration is the potential bias in parameter estimates when utilizing the unweighted LCCA model, which may lead to biased class sizes, and under- or over-representation of certain population segments (Asparouhov, 2005). Therefore, it is critical to apply weights in such models. For a detailed discussion on various weighting methods and a comparison of their results, please refer to the full version of the journal paper. The following sections will focus solely on the selected optimal method: the quasi-maximum likelihood (or pseudo-maximum likelihood) approach, where the model was estimated using quasi-maximum likelihood estimators on weighted cases.

4.5 Results and Discussions

After conducting latent class models with varying numbers of classes, ranging from two to six, I determined that a four-class solution provided the optimal balance between goodness-of-fit and interpretability. I evaluated the models using several measures, along with their respective values (see Table 4-1). Lower values of AIC, BIC, and ABIC indicate a better model fit, while higher entropy values suggest improved class separation (Collins & Lanza, 2010; Goulias & Henson, 2006). The minimum class size was also considered as a criterion for model selection. Ultimately, I opted for the four-class solution as the most optimal.

Table 4-1 LCCA model fit statistics

Model	npar	Entropy	Minimum Class Size (%)	−2LL	AIC	BIC	Adj. BIC
2-class	41	0.876	34.2%	-106895.2	213872.5	214147.1	214016.8
3-class	52	0.835	20.8%	-105008.2	210120.3	210468.6	210303.4
4-class	**63**	**0.805**	**9.8%**	**-104125.2**	**208376.5**	**208798.4**	**208598.2**
5-class	74	0.786	6.3%	-103723.9	207595.8	208091.4	207856.3
6-class	85	0.750	3.4%	-103446.1	207062.3	207631.5	207361.4

Note: Bold indicates the best fitting class; npar: number of parameters; −2LL: −2 log likelihood; AIC: Akaike information criterion; BIC: Bayesian information criterion; Adj. BIC: adjusted Bayesian information criterion.

Detailed regression coefficients from the measurement model are provided in the full journal paper. However, Table 4-2 and Figure 4-3 below compare the trip frequency and the trip distance across different travel modes and traveler groups. The classification aligns with a previous study conducted in California (Lee et al., 2020).

Table 4-2 One-week trip frequencies by travel modes, trip purposes, and class of travelers

	Class 1 Drive-alone Users	Class 2 Carpoolers	Class 3 Transit Users	Class 4 Cyclists	Weighted sample average
Probability-weighted sample size	2,678	1,410	750	215	5,053
Percentage of total sample	53.0%	27.9%	14.8%	4.3%	100%
SOV Work trips	**6.31**	1.30	0.05	2.35	4.06
SOV Non-work trips	**15.62**	5.11	0.51	8.67	10.99
Carpool Work trips	0.72	**4.75**	0.26	0.63	0.80
Carpool Non-work trips	10.48	**20.59**	4.16	8.38	9.39
Transit Work trips	0.00	0.00	**1.14**	0.65	0.35
Transit Non-work trips	0.06	0.32	**6.43**	2.41	1.67
Biking Work trips	0.02	0.01	0.63	**0.96**	0.37
Biking Non-work trips	0.21	0.19	1.71	**2.20**	0.99
Walking Work trips	0.77	1.23	**4.53**	3.02	1.98
Walking Non-work trips	3.53	5.85	**18.06**	11.17	7.92
Average Total weekly trips	37.73	39.34	37.49	**40.45**	38.52
Average total work trips	**7.83**	7.28	6.62	7.60	7.56
Average total non-work trips	29.90	32.06	30.87	**32.84**	30.96

Note: Values in **bold** indicate the highest value for each row.

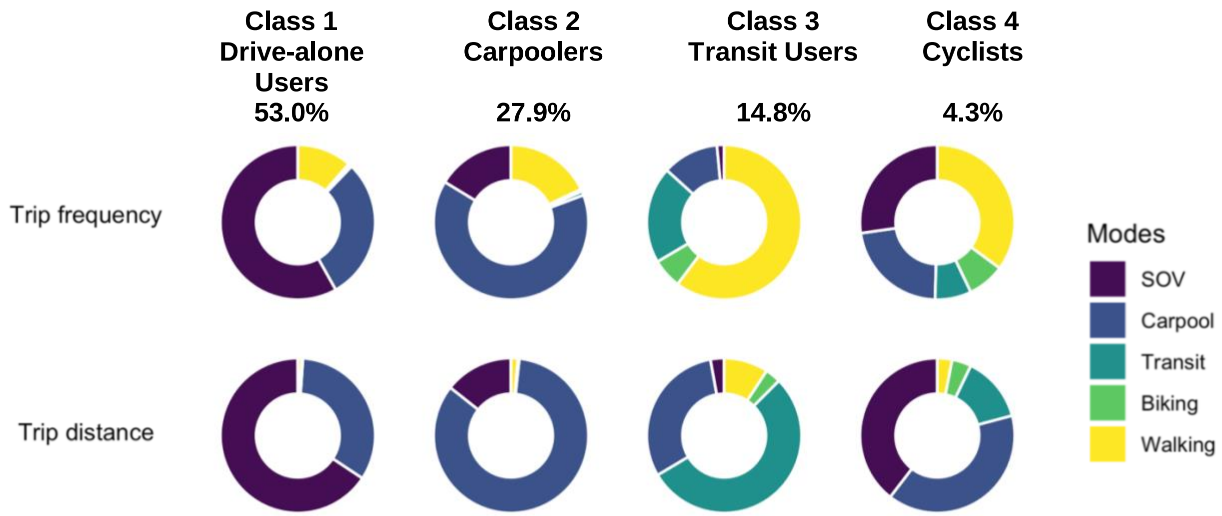


Figure 4-3 The weighted distributions of trip frequencies and trip distances across travel means, separately for each class

Class 1, Drive-alone Users (53.0%), have significantly higher trip frequencies and VMT by SOV for both work and non-work purposes. However, their usage of public transit and active modes is relatively minimal. ***Class 2, Carpoolers (27.9%)***, predominantly use carpooling, especially for non-work trips.

Class 3, Transit Users (14.8%), engage in the highest number of transit and walking trips, while maintaining the lowest frequency of car-based trips. Notably, their frequency of non-work walking trips is the highest among all trip types. Finally, ***Class 4, Cyclists (4.3%)***, have the highest frequency of biking trips compared to other groups, alongside a moderate number of trips using all other modes. Consistent with previous findings, automobiles and transit remain important for cyclists when bicycling is not a suitable option (Kuhnimhof et al., 2010). Evidently, *Transit Users,* and *Cyclists* are more multimodal than the two groups of *Car Users,* showcasing a more balanced distribution of trip frequency and distance across various modes.

The class membership model explores the factors that influence the likelihood of individuals belonging to a particular class and provides a comprehensive overview of the class-specific profiles. ***Drive-alone Users*** primarily consist of individuals aged 35 or older (71%). This class has a high proportion of full-time employees. As expected, respondents in this class are mainly drivers and have the highest number of vehicles per household worker, which explains their frequent reliance on driving alone. In fact, this class has the highest share of individuals living in low-density home locations and working in low job density working locations. Interestingly, I also observe lower job density in their home locations (a variable excluded from the model because of high multicollinearity). This suggests a higher chance of worker-job spatial mismatch, which likely explains their heavy reliance on automobiles for work purposes. Overall, the profile of this group aligns with the profile of "monomodal drivers" identified in previous studies (Lee et al., 2020; Ralph, 2017). ***Carpoolers***, on the other hand, tend to be younger, with 61% of them under the age of 35. They have the fewest vehicles and have the highest proportion of individuals without a driver's license. This explains their extensive use of carpooling, especially for non-work trips. In comparison to *Drive-alone Users*, *Carpoolers* are more likely to live in densely populated areas and work in areas with high job density. The profile of ***Transit Users*** is notably different from that of ***Drive-alone Users***. They are the least car-dependent group among all the classes. ***Transit users*** and ***Cyclists*** share some similarities, but they also have distinguishing characteristics. While *Transit Users* have the lowest proportion of white individuals (18%), *Cyclists* are in fact, predominantly white (39%). Similarly, *Transit Users* have a higher representation of women, whereas *Cyclists* have a higher proportion of men. This disparity may be influenced by factors such as the physical demands and perceived risks associated with cycling. Moreover, *Cyclists* tend to have higher education and income compared to *Transit Users*. Finally, *Cyclists* are also more likely to work in areas with high job density, which is usually an indicator of more diverse land use and better transportation infrastructure. This aligns with existing studies that highlight the positive association between higher-density built environments and less auto-oriented lifestyles (T. Chowdhury & Scott, 2020; Schneider, 2015).

Table 4-3 Class Membership Model (base: Drive-alone users) & weighted summary statistics of covariates by classes

	Carpooler		Transit users		Cyclists		Weighted distribution across Classes (column-wise)				
	Est.	**Sig.**	**Est.**	**Sig.**	**Est.**	**Sig.**	**Drive-alone users**	**Carpoolers**	**Transit riders**	**Cyclists**	**Weighted sample average**
Intercept	-2.282		-1.226		3.366	**					
<u>Demographics</u>											
Age											
18-34							29.1%	**60.9%**	31.2%	40.9%	33.7%
35-54	-0.342		0.604		0.053		47.5%	31.2%	**57.2%**	46.3%	46.9%
55-64	-1.247	***	0.701		-0.876		**16.5%**	6.1%	11.6%	8.5%	13.9%
65 or over	-1.203	*	-26.539	***	-0.801		**6.8%**	1.7%	0.0%	4.4%	5.5%
Race/Ethnicity											
White (non-Hispanic)							38.8%	26.0%	18.0%	**54.7%**	39.2%
Black or African American (non-Hispanic)	-1.761	**	-29.35	***	-0.414		7.3%	**8.6%**	0.0%	2.5%	5.9%
Asian (non-Hispanic)	-1.601	***	1.075	*	-1.58	**	26.6%	28.1%	**41.4%**	19.3%	26.5%
Hispanic, Latino, or Spanish origin	-1.019	**	0.588		-2.188	***	26.6%	36.9%	**40.6%**	20.5%	27.3%
Other (non-Hispanic)	0.584		-1.363		-0.204		0.7%	0.5%	0.0%	**3.1%**	1.1%
Gender											
Female							51.7%	**64.9%**	52.0%	35.1%	49.6%
Male	0.976	***	-0.063		-0.49		48.3%	35.1%	48.0%	**64.9%**	50.4%
Education											
Some College or lower							32.2%	35.8%	**48.0%**	18.8%	31.2%
Bachelor	0.025		0.178		1.252	**	**36.7%**	**37.2%**	35.5%	35.4%	36.4%
Higher than Bachelor	0.263		-0.661		1.054		31.2%	27.0%	16.5%	**45.8%**	32.4%
Driver's license											
No							1.6%	**39.2%**	20.7%	1.2%	5.7%
Yes	-0.838		-2.753	***	-5.71	***	98.4%	60.8%	79.3%	**98.8%**	94.3%
Employment											
Full-time employees							**84.6%**	69.1%	79.2%	83.7%	82.9%
Part-time employees	0.95	**	0.13		0.928		12.0%	**29.4%**	15.6%	14.6%	14.0%
Primarily self-employed/ unpaid volunteer or intern	0.199		1.468		-0.255		3.4%	1.5%	**5.2%**	1.8%	3.1%
<u>Household socio-economic status</u>											

Adjusted household income (adjusted by household composition and cost of living)											
1st quartile							29.2%	**46.8%**	42.8%	11.5%	28.2%
2nd quartile	-1.628	***	-0.185		0.594		28.4%	22.3%	28.7%	**34.3%**	29.1%
3rd quartile	-1.308	**	-0.396		0.189		29.7%	16.6%	22.6%	**30.9%**	28.4%
4th quartile	-1.474	**	-0.455		0.168		12.8%	14.4%	5.9%	**23.3%**	14.3%
Number of household vehicle per employee	-0.386		-0.683		-6.683	***	**1.2**	0.3	1.0	1.0	1.1
<u>Travel demand management</u>											
Employer-provided transit subsidy											
No							**87.6%**	78.2%	79.6%	65.6%	82.2%
Yes	1.159	***	0.723		1.294	**	12.4%	**21.8%**	20.4%	34.4%	17.8%
Employer-provided TNC subsidy											
No							90.7%	**98.7%**	93.1%	94.6%	92.2%
Yes	-1.738	***	-1.028		-3.066	***	**9.3%**	1.3%	6.9%	5.4%	7.8%
Employer-provided other subsidies											
No							**93.9%**	83.7%	86.6%	80.4%	90.1%
Yes	1.625	***	1.507	*	2.14	***	6.1%	16.3%	13.4%	**19.6%**	9.9%
<u>Region & Built environment characteristics</u>											
Region											
Nine-county Bay Area							32.5%	63.3%	27.2%	**62.1%**	39.8%
Six-county SACOG planning area	-1.176	***	0.51		-4.716		**7.1%**	0.6%	4.7%	3.9%	5.9%
San Diego County	-2.142	***	1.011		-4.582	***	**18.4%**	3.1%	34.4%	6.9%	16.4%
Los Angeles and Orange counties	-1.436	***	-0.158		-1.02	*	**42.0%**	33.0%	33.7%	27.1%	37.9%
Residential location population density											
1st quartile							**14.5%**	4.5%	10.3%	12.1%	13.0%
2nd quartile	0.291		-0.84		1.103		**21.6%**	8.2%	12.5%	15.8%	18.8%
3rd quartile	0.605		-0.322		1.07		**33.0%**	16.7%	18.9%	26.8%	29.5%
4th quartile	1.179	**	1.271	*	1.533	*	30.9%	**70.6%**	58.4%	45.3%	38.6%
Work location job density											
1st quartile							**5.6%**	5.0%	2.3%	2.0%	4.6%
2nd quartile	-1.772		1.781		2.863		7.6%	2.8%	**13.9%**	0.7%	6.5%
3rd quartile	-1.243		1.891		3.188		17.1%	6.9%	**18.9%**	5.1%	14.3%
4th quartile	0.859		1.365		4.405	***	69.6%	85.4%	64.9%	**92.2%**	74.6%

Notes:
1. Sig. in the table denotes the significance level (* at the 10% level, ** at the 5% level, and *** at the 1% level).
2. Bold values in the table indicate the highest value for each row.

With a better understanding of the profiles of each of the four identified traveler groups, I can now delve into the distinct characteristics of ridehailing trips among these groups. I observed a total of 3,964 unweighted TNC trips by individuals included in the analysis. However, this number was adjusted to 1,839 trips after applying weights, as both surveys had intentionally oversampled TNC trips. Table 4-4 provides class-specific probability-weighted summary statistics for TNC trips during the survey period. Class 3, which consists of transit users and pedestrians, made 39% of these trips. *Carpoolers, Cyclists*, and *Drive-alone Users* accounted for 33%, 28% and 9% of the TNC trips, respectively. *Transit Users* are more likely to be TNC users, as evidenced by both self-reported monthly ridehailing travel frequency and the number of TNC trips observed during the survey period. Consistently, *Transit Users* have the highest average weekly frequency of ridehailing trips.

Regarding the type of ridehailing service used, *Transit Users* are more likely to use pooled ridehailing, while *Drive-alone Users* are more inclined to use regular economy, and premium services. *Drive-alone Users* also tend to schedule their trips in advance with a specific pick-up time. In terms of temporal patterns, *Drive-alone Users* are more likely to take ridehailing trips during weekends compared to other groups. Although most ridehailing trips across all classes start in the afternoon and evening, *Transit Users* are more likely to travel in the morning and midday compared to the average. On the other hand, car users (*Driver-alone Users* and *Carpoolers*) tend to take their trips in the afternoon, evening, and late at night. These differences in timing appear to be related to trip purposes. For instance, *Transit Users* and *Cyclists* are more likely to use ridehailing for mandatory trips (e.g., commuting), while car users are more likely to use it for recreational purposes later in the day. Moreover, *Transit Users* show higher proportions (5% and 7%) of TNC trips starting and ending with a travel mode switch, indicating that TNC services are more likely to be the access/egress mode for them.

Finally, if ridehailing services were not available, individuals from different classes would have chosen different means of travel. The findings suggest that individuals within each traveler group would highly likely have chosen the mode that is most commonly used by their respective group. For instance, if ridehailing were not an option, car users would likely have taken taxis, driven their own cars, or shared rides with others, while *Transit Users* would still prefer transit as their primary alternative (Tarabay & Abou-Zeid, 2020). However, cyclists would likely ride with others.

Table 4-4 TNC user distribution and trip characteristics by classes

	Class 1 *Drive-alone users*	**Class 2** *Carpoolers*	**Class 3** *Transit users*	**Class 4** *Cyclists*	*Sample average*
N (individuals, weighted)	2,678	1,410	750	215	5,053
% (individuals, weighted)	53.0%	27.9%	14.8%	4.3%	100.0%
N (TNC trips, weighted)	516	602	721	160	1,839
% (TNC trips, weighted)	28.1%	32.7%	39.2%	8.7%	100.0%
TNC user group (based on self-reported monthly TNC usage frequency)					
Non-user (less than 1 day per month)	**62.5%**	49.0%	39.4%	50.7%	57.4%
Occasional users (1-3 days per month)	35.4%	**42.6%**	25.4%	**43.1%**	36.6%
Frequent users (4+ days per month)	2.1%	8.3%	**35.2%**	6.2%	5.9%
TNC user group (based on observed one-week trip frequency in travel diary)					
Non-user (0 times per week)	**92.5%**	74.6%	49.1%	83.0%	85.4%
Users (1 time per week)	2.2%	**7.5%**	**7.3%**	4.4%	3.7%
Users (2-3 time per week)	4.7%	13.9%	**22.4%**	11.6%	8.2%
Users (4+ time per week)	0.6%	4.0%	**21.3%**	1.0%	2.7%
Average one-week TNC trip frequency					
Among entire sample from 4 MPOs	0.2	0.4	**1.0**	0.7	0.4
TNC service type (only in 3 MPOs)					
Pooled (e.g., UberPOOL, Lyft Line)	11.3%	27.4%	**37.5%**	35.9%	27.6%
Regular or economy (e.g., UberX, Lyft)	**86.8%**	65.2%	62.0%	64.0%	69.4%
Premium (e.g., UberSELECT)	**0.6%**	0.5%	0.2%	0.01%	0.4%
Unknown	1.4%	**6.9%**	0.4%	0.01%	2.6%
Scheduled TNC trip in advance for a specific pick-up time (only in 3 MPOs)					
No	95.6%	97.1%	**98.9%**	96.7%	97%
Yes	**4.4%**	2.9%	1.1%	3.3%	3.4%
Day of the week					
Weekday	62.3%	77.1%	73.5%	**82.7%**	72.4%
Weekend	**37.7%**	22.9%	26.5%	17.3%	27.6%
Time of the day					
Morning (5 am – 10 am)	11.8%	**24.9%**	20.4%	11.8%	18.9%
Midday (10 am – 3 pm)	6.9%	19.0%	**24.2%**	20.5%	17.9%
Afternoon (3 pm – 7 pm)	21.4%	**24.0%**	**23.9%**	36.8%	24.3%
Evening (7 pm – 11 pm)	**41.9%**	22.9%	22.5%	10.3%	26.6%
Night (11 pm – 5 am)	17.9%	9.2%	9.1%	**20.7%**	12.3%
Activities at TNC trip origin					
Home	**37.0%**	30.3%	27.1%	19.2%	30.0%
Mandatory	7.3%	17.5%	22.3%	**28.4%**	17.5%
Recreation	**45.4%**	35.4%	33.4%	25.4%	36.5%
Maintenance/escort/errand/other	8.9%	9.6%	12.6%	**26.9%**	11.9%
Changing travel mode	1.5%	7.1%	4.6%	0.1%	4.2%
Activities at TNC trip destination					
Home	30.9%	26.5%	36.4%	**44.4%**	32.6%
Mandatory (school/work trips)	9.2%	**33.7%**	24.2%	5.2%	21.7%
Recreation	**47.3%**	24.3%	25.5%	24.9%	30.7%

	Class 1 *Drive-alone users*	Class 2 *Carpoolers*	Class 3 *Transit users*	Class 4 *Cyclists*	*Sample average*
N (individuals, weighted)	2,678	1,410	750	215	5,053
% (individuals, weighted)	53.0%	27.9%	14.8%	4.3%	100.0%
N (TNC trips, weighted)	516	602	721	160	1,839
% (TNC trips, weighted)	28.1%	32.7%	39.2%	8.7%	100.0%
Maintenance/escort/errand/other	10.8%	9.2%	7.2%	**25.5%**	10.2%
Change travel mode	1.8%	6.3%	**6.7%**	0.0%	4.8%
Alternative means of travel were ridehailing not available					
Make same trip by using a taxi	32.3%	**34.8%**	21.7%	14.0%	27.7%
Make same trip by driving own car	**38.0%**	23.5%	7.1%	1.3%	19.5%
Make same trip by riding with others	13.1%	7.9%	2.6%	**65.7%**	11.8%
Make same trip by using transit	5.5%	16.0%	**38.6%**	2.5%	20.5%
Make same trip by walking/biking	5.2%	8.8%	**12.0%**	11.1%	9.2%
Travel to a different place instead	0.3%	1.0%	1.6%	**4.0%**	1.3%
NOT make the trip at all	4.3%	4.3%	**15.6%**	0.0%	8.1%
Other	1.3%	**3.7%**	0.9%	1.2%	1.9%

Note: **Bold** values in the table indicate the highest value for each row.

4.6 Conclusion

In this study, I performed a weighted latent-class cluster analysis based on the week-long GPS-based travel diaries of 5,053 commuters in four metropolitan regions in the state of California. I identified four classes of travelers with unique travel mode preferences. Among four traveler groups, *Drive-alone Users (53% of total weighted sample)* and *Carpoolers (28%)* exhibit more car-oriented but less multimodal mode-use patterns, while *Transit Users (15%)* and *Cyclists (4%)* show less car-oriented but more multimodal travel patterns. Each traveler group has a unique profile in terms of sociodemographic characteristics, built-environment attributes, and employer-provided mobility subsidies.

The result of the traveler classification aligns with previous research conducted in California, although there are variations in class sizes and distributions between the two studies (Y. Lee et al., 2020). This confirms the existence of four predominant traveler groups within the state. However, upon cross-comparing Lee et al.'s study, it becomes evident that travelers within these four MPOs are overall less car-dependent and more multimodal compared to travelers in the rest of the state. It is crucial to target and tailor policies for the specific group of travelers. Policymakers should pay special attention to multimodal travelers, as they have greater inclination to embrace alternative travel modes beyond cars.

I also examined the adoption, frequency, trip attributes, and substitution patterns of ridehailing for each traveler group to better understand the associations among ridehailing, other travel modes, and their impacts on the environment. Transit Users demonstrate the highest likelihood of utilizing ridehailing services. This preference can be attributed to the fact that they have the lowest household vehicle ownership, while ridehailing provides them with on-demand automobility, enabling convenient access to various activities and opportunities (Brown, 2019). In fact, *Transit Users* are more likely to use ridehailing for mandatory trips (e.g., commuting to work) and for access and egress connection to other modes (King et al., 2020). However, the dataset indicates that ridehailing trips directly connecting to transit remain exceedingly uncommon (constituting only around 3% of all ridehailing trips in the sample).

To better comprehend the synergistic relationship between these two modes, future data collection efforts should be specifically designed to explore this aspect.

This study further uncovers the travel patterns, multimodality, and modal substitution associated with ridehailing use. One key finding is that, in the absence of ridehailing, individuals primarily rely on taxis (28%), public transit (21%) and personal cars (19%) as their primary modes of transportation. Interestingly, individuals tend to opt for their most frequently chosen mode of travel if ridehailing were not available – for instance, car-users gravitate towards car-based modes, while transit users continue to use transit. As a result, the net environmental impacts resulting from ridehailing-induced modal substitutions remain unclear.

On one hand, substituting other motorized modes with ridehailing does not necessarily lead to lower emissions; in fact, it might very well have the opposite effect. For instance, *Drive-alone Users* and *Carpoolers*, who are part of the car-oriented traveler groups, tend to use ridehailing less frequently and are less likely to opt for pooled options when they do use the service. Moreover, when using ridehailing, they are more likely to lean towards premium services that contribute more to congestions (Dhanorkar & Burtch, 2021) and are typically associated with less fuel-efficient vehicles compared to regular or pooled ridehailing (i.e., ridesplitting) services (W. Li et al., 2021; Zoepf et al., 2018). The uncertainty surrounding the environmental impact of ridehailing modal substitution is further exemplified when considering the two less car-oriented traveler groups: *Transit Users* and *Cyclists*. These groups have a higher tendency to substitute ridehailing for transit and/or active modes, and they also use ridehailing more frequently. However, members within these two groups are also more likely to opt for pooled ridehailing services, which consume less energy and produce less GHG on average.

These findings align with previous research on the heterogeneous emission impacts of ridehailing services, taking into account factors such as trip characteristics and built environment factors. For instance, For instance, Li et al. (2021) emphasized the significant emission reduction benefits of pooled ridehailing (i.e., ridesplitting) compared to regular ridehailing. The characteristics of the built environment in which ridehailing trips take place (e.g., density of expressways and diversity of land use) also show a significant association with ridehailing emissions. Chen et al. (2021) further indicated that the scale of ridehailing drivers and riders, and the travel demand in a particular region can influence the proportion of deadheading miles (which occur when ridehailing drivers cruise without passengers), which in turn impacts the emission performance of the ride-hailing system. Moreover, Tikoudis et al. (2021) highlighted that in car-dependent areas, strong preferences for private cars create substantial barriers to the adoption of ridehailing, thereby limiting its potential environmental benefits. Conversely, in regions where public transport and active modes of transportation are more prevalent, ridehailing has the potential to attract transit riders, leading to a net increase in GHG emissions.

Acknowledging the absence of a standardized formula to effectively minimize the environmental impacts of ridehailing services, the objective is to provide a more accurate depiction of the role of ridehailing within individuals' complete travel routines (by using accurate and highly precise trip recording via GPS devises), enabling planners and policymakers to make informed decisions. Furthermore, the results can assist practitioners in identifying ridehailing trips that should be promoted (e.g., those occurring in areas or at times with limited transit options) versus those that should be discouraged (e.g., those conducted when viable, less polluting alternatives are available). This approach aims to reduce ridehailing environmental impacts while harnessing its mobility-enhancing potential (Young et al., 2020).

Lastly, it is important to acknowledge some limitations of this study. First, to obtain a larger sample size, I merged two datasets from two surveys. Although these two surveys share many similarities (e.g., questionnaire design, sampling strategies, data collection methods, and weighting techniques), there may still be slight differences. For instance, the 2018 Sacramento Regional Transportation Study was conducted slightly earlier than the 2019 California TNC User Survey in the other three regions. Consequently, the estimated ridehailing mode share in the Sacramento region might be lower than the actual figure if the survey had instead been conducted in 2019 as well. Secondly, as a cross-sectional analysis, this study does not establish a causal relationship between travel modality and the adoption and use of ridehailing. To determine causality, researchers would need to develop a longitudinal study that investigates whether changes in travel modality led to changes in the adoption and use of ridehailing (or vice versa). I believe this would be a relevant direction for future research endeavors. Thirdly, while I discussed the merits of restricting this study to respondents with complete seven-day trip information, this decision resulted in the omission of a sizable number of observations from the datasets. Consequently, some ridehailing trips collected in the dataset were not fully utilized in this study. Finally, this dataset lacks attitudinal information towards car-dependence, active lifestyles, the adoption of new technologies, and environmental concerns, which previous studies have shown to play a significant role in influencing travel modality. To objectively capture travel patterns and incorporate individuals' psychometrical characteristics, it would be beneficial to combine GPS tracking data like the dataset used in this study with more comprehensive questionnaires.

Acknowledgments

This study was made possible through a research grant [grant ID: 19STC006] from the California Air Resources Board (CARB). Additional funding was provided by the 3 Revolutions Future Mobility Program of the University of California, Davis. The data for this study was collected by SACOG, SANDAG, SCAG, MTC, and SFCTA as part of a Sustainable Transportation Planning Grant from the California Department of Transportation (Caltrans). Special thanks to Yongsung Lee, Mischa Young, Junia Compostella, Giovanni Circella, and Alan Jenn for their invaluable contributions as coauthors of this study. I extend my sincere gratitude to Melanie Zauscher, Annalisa Schilla, Krystal Ayala, Danielle Kochman, Wu Sun, Grace Mino, Bhargava Sana, Shimon Israel, Bill Davidson, Yang Wang, Joe Castiglione, Shengyi Gao, Purva Singh, and Bruce Griesenbeck for their support for this project.

5 Motivations and Barriers to Electrifying Ridehailing Services: Insights from a Survey of TNC Drivers in California

5.1 Abstract

The promotion of zero-emission vehicles (ZEVs), particularly BEVs has been a cornerstone in efforts to decarbonize passenger transportation. Due to the average high mileage driven by ridehailing fleets and the substantial GHG emissions from current gas-powered vehicles, transitioning to ZEVs within this sector has the potential to generate substantial economic, environmental, and public health benefits. In California, the Clean Miles Standard program highlights fleet electrification as a critical strategy for reducing GHG emissions within the ridehailing sector. This study uses data from a web-based survey of ridehailing drivers in California conducted with the support from Uber and Lyft, to understand drivers' motivations and barriers to EV adoption. An integrated choice and latent variable (ICLV) model was estimated to (1) identify the factors motivating ridehailing drivers to obtain a vehicle with the intention of ridehailing work; (2) explore the factors impacting the vehicle fuel type choices for drivers with or without such ridehailing intentions; (3) quantify the impact of EV incentives and charging infrastructure on promoting EV adoption. Older drivers, those solely working for ridehailing, and renters in multi-family dwellings are more likely to obtain vehicles for ridehailing work. Additionally, BEV adoption is highly correlated with latent factors such as positive *attitude* towards EV and favorable *subjective norm* around, while *perceived barriers* to EVs hinder their adoption. Vehicles leased or rented through TNC rental programs are more likely to be EVs. Home chargers have a stronger impact among drivers who obtained their vehicle without ridehailing intention, while public chargers are more essential for those who acquire the vehicle with the ridehailing intention. Federal incentives have a more substantial impact on EV adoption compared to state and local incentives, although their effectiveness depends on the drivers' familiarity with the programs. The impact of federal incentives is especially pronounced among

drivers who acquired the vehicle with ridehailing intention, with a potential 10 percentage point increase in BEV market share if all drivers were very familiar with these incentives.

5.2 Introduction

Promoting zero-emissions vehicles (ZEVs), particularly BEVs, has been a key component of efforts to decarbonize passenger transportation. While extensive research has explored EV adoption among private vehicles in the general population (Mandev et al., 2022; Iogansen et al., 2023) and within taxi fleets operated by professional drivers (Hagman & Langbroek, 2019; Kinsella et al., 2023), limited research has focused on ridehailing fleets. These fleets are typically comprised of vehicles owned and operated by drivers contracted with transportation network companies (TNCs) like Uber and Lyft.

Ridehailing fleets, which typically have relatively high mileage, stand out as one of the most promising niche markets for EVs (Yu et al., 2017). Recent studies highlight the potential economic, environmental, and public health benefits of such a transition (Hunt & McKearnan, 2020; Jenn, 2019; Sarasini & Linder, 2018; Sprei, 2018; Yu et al., 2017; Zhou et al., 2021). Furthermore, by using EVs to transport passengers, the ridehailing sector can enhance public awareness and increase consumer exposure to EVs, thereby accelerating the transition to cleaner vehicles among the public (Hall et al., 2021). Despite the advantages of EVs, such as reduced fuel and maintenance costs, many ridehailing drivers continue to encounter challenges to adoption. Notable barriers include limited driving range, high upfront purchase costs, and insufficient access to reliable and affordable charging infrastructure (Moniot et al., 2019; Rajagopal & Yang, 2020; Weiss et al., 2019).

The CARB estimated that in 2018, ridehailing vehicles in the state emitted an average of 301 grams of CO_2-equivalent per passenger-mile traveled (PMT), approximately 50% higher than the emissions from passenger vehicles (203 g CO_2-eq/PMT) (California Air Resources Board, 2019). In response, California introduced the Clean Miles Standard (CMS) Program (Senate Bill (SB) 1014), becoming the first state in the US to regulate GHG emissions and establish GHG/PMT targets specifically for ridehailing fleets. CARB identified four key strategies to help reach these targets: promoting vehicle electrification, increasing ride-pooling, decreasing deadheading, and integrating ridehailing with public and active transportation modes. To accelerate vehicle electrification, California set annual targets to increase the percentage of TNC miles traveled by ZEVs to 90% by 2030. Although EVs accounted for fewer than 0.5% of active ridehailing vehicles and less than 1% of miles traveled across major TNCs in California in 2018, both Uber and Lyft have committed to achieving 100% electrification of their fleets by 2030 (Slowik et al., 2019).

To the authors' best knowledge, no study to date has systematically examined the motivating factors and barriers to EV adoption among ridehailing drivers in the US, and how these factors vary across different driver groups. Moreover, despite numerous monetary incentives and supporting programs from federal, state, and local governments (as well as TNCs), to promote EV adoption, there has yet to be a study that has quantified the level of awareness or utilization of these incentives among drivers or examined how they impact drivers' vehicle fuel type choices. Ridehailing drivers exhibit significant heterogeneity, comprising both full-time drivers and those who only drive part-time or occasionally (Rajagopal & Yang, 2020). Additionally, some drivers may obtain vehicles specifically dedicated to ridehailing work, prioritizing features like higher fuel efficiency and larger luggage capacity, while others may use their existing vehicles that are used for both ridehailing work and to meet household needs. As a result, the determinants of vehicle fuel type are likely to vary between drivers who obtained their vehicles with the intention of using them for ridehailing work and those who did not. Moreover, the impacts of incentives on EV adoption could differ based on whether a vehicle was purchased with the intention to use it for ridehailing work.

This study aims to examine the factors impacting ridehailing drivers' fuel type choices for their ridehailing vehicles. Using data collected through a web-based survey of ridehailing drivers in California, I employ descriptive analyses and an integrated choice and latent variable (ICLV) model to address three key research questions: (1) How do sociodemographic characteristics impact ridehailing drivers' decisions to obtain a vehicle with the intention of using it for ridehailing work? (2) What factors affect vehicle fuel type choices among drivers with and without such ridehailing intention? (3) To what extent can EV incentives and charging infrastructure drive greater EV adoption? The insights gained from this study can inform government and industry policies aimed at accelerating the electrification of ridehailing fleets.

The remainder of the chapter is structured as follows. Section 5.3 reviews relevant literature on EV adoption among ridehailing drivers. Section 5.4 describes the survey data, provides descriptive analyses, presents the modeling framework, and summarizes key sample statistics. Section 5.5 presents the results and discussion of key findings. Finally, Section 5.6 concludes with a summary of the main insights and offers policy recommendations.

5.3 Literature Review

A limited number of cities outside of the US have implemented policies to accelerate the transition of ridehailing fleets away from internal combustion engine vehicles (ICEVs). For instance, Shenzhen mandated that all newly registered ridehailing vehicles must be fully electric (Justice Bureau of Shenzhen Municipality, 2021). However, research in the Chinese ridehailing market indicates that many drivers do not perceive an urgent need to switch to EVs (Zhou et al., 2021), and some have even quit ridehailing work due to such requirements (Du et al., 2020). To effectively accelerate EV adoption within the US ridehailing market while minimizing potential adverse impacts on drivers, it is essential to understand drivers' motivations and address the barriers they encounter.

Since most drivers use their own vehicles for ridehailing work, their choice of vehicle fuel type is likely impacted by their socio-demographic characteristics and household vehicle ownership patterns (Rajagopal & Yang, 2020; Sanguinetti & Kurani, 2021). Du et al. (2020) and Bansal et al. (2020) found that EV acceptance is higher among younger drivers, regular drivers, individuals with higher educational attainment and income, metropolitan residents, and those driving vehicles they own or are provided by the

TNC platforms (as opposed to rented or leased vehicles from other sources). However, many drivers earn below-average incomes, which poses a significant barrier to acquiring an EV (Rajagopal & Yang, 2020; Weiss et al., 2019).

Acceptance of EVs among drivers can be influenced by how far and how often they travel while working, and the number of trips that they serve. Du et al. (2020) found that current EV drivers with shorter daily travel distances (less than 155 miles) show higher acceptance, as EVs can meet their travel needs without recharging. However, this trend is reversed for non-EV drivers, as shorter travel distances indicate fewer trip requests, making a transition to EVs less financially advantageous. Moreover, Taiebat et al. (2022) suggests that BEVs with a range of at least 250 miles are more suitable for ridehailing drivers compared to shorter-range BEVs.

The availability and adequacy of charging infrastructure remain critical challenges (Jenn, 2024; Liu et al., 2022). This could be a notable barrier for ridehailing drivers using EVs, as mid-shift charging during work hours directly reduces their revenue. While overnight charging can substantially reduce downtime (Moniot et al., 2019; Pavlenko et al., 2019), many drivers are underserved by home charging infrastructure. This issue is especially pronounced for those living in multi-family dwellings that lack dedicated parking spaces equipped with electrical outlets (Nicholas et al., 2020). Additionally, low-income communities, where many ridehailing drives reside, often have lower public charger coverage (Hsu & Fingerman, 2021).

EV-related incentives play a pivotal role in promoting EV adoption among ridehailing drivers, who often view these incentives as critical motivations for transitioning to EVs (Du et al., 2020). In terms of supporting programs, Ku et al. (2024) demonstrates that EV rental services not only effectively foster EV adoption but may also increase drivers' net earnings.

Finally, an increasing body of research suggests that attitudes and perceptions influence EV adoption among ridehailing drivers. For instance, Zhou et al. (2021) applied the theory of perceived value and found that *functional values, emotional values,* and *social values* positively correlate with drivers' intention to purchase an EV. The authors also found that *functional risks*, *financial risks,* and *physical/mental risks* negatively impact purchase intentions.

5.4 Data and Methods

5.4.1 California Ridehailing Driver Survey

The research team directly collaborated with Uber and Lyft, the two largest TNCs in the US, to recruit ridehailing drivers across California. A web-based survey was administered between July 2023 and June 2024, capturing a wide range of information on ridehailing drivers, including their sociodemographic and economic characteristics, detailed profiles of the vehicles they use for ridehailing work, their service areas and duration of work as ridehailing drivers, and experiences with ZEVs.

The research team implemented a stratified random sampling approach based on key driver characteristics: *region of residence* (Bay area, Sacramento, South California, San Diego, and the rest of the state), *tenure on the TNC platform* (<2 years, 2 to 5.5 years, >5.5 years), and *average weekly working hours for ridehailing* (occasional drivers: <10 hours, par-time drivers: 10 to 25 hours, full-time drivers: >25 hours). The original target sample size is 2,000 drivers (1,500 from Uber and 500 from Lyft due to the different size of driver pool each company has). The TNCs calculate the sample size for each stratum by multiplying the proportion of drivers by the respective target sample size. The team decided to adjust the sample size to over-sample regions with fewer drivers (i.e., original sample size times 2) and under-sample regions with more drivers (i.e., original sample size divided by two). Based on the TNCs' previous survey experience, full-time drivers have a higher response rate, the team thus assumed a 7% response rate among full-time drivers and 5% among part-time and occasional drivers. Based on this information, the team computed the total number of drivers to be invited to participate in the study from each stratum. Invitations to participate in the survey were distributed directly by Uber and Lyft, and drivers received an $8 gift card from their choice of a selection of vendors after completing the survey.

To improve the representativeness of the sample relative to the broader population of ridehailing drivers in California, the team applied a weighting technique that incorporated cell weighting and iterative proportional fitting for the full sample[8]. This process was implemented using the *mipfp* R package (Barthélemy & Suesse, 2018). After rigorous data quality checks, the final sample for this study includes 1,099 drivers. All descriptive analyses presented in the subsequent sections are based on this weighted dataset, representing the trends among the target driver population.

5.4.2 Characteristics of Household and Ridehailing Vehicles of TNC Drivers

This section provides summary statistics of household vehicles and ridehailing vehicles (regardless of whether they acquired a vehicle that was dedicated to ridehailing) of each TNC driver.

(1) Availability and Fuel Type Choice of Household and Ridehailing Vehicles

Drivers were asked to report the number of passenger vehicles that they *or anyone in their household* currently has access to (owned, leased, rented, borrowed, company-owned, etc.) and the fuel type of each vehicle. As shown in

Table 5-1, nearly 40% of the 1,099 ridehailing drivers (and their household members) currently have access to only one passenger vehicle. Then, drivers reported the number of vehicles (up to three) that they currently have registered with a TNC and details of each vehicle. Nearly 90% of drivers only registered one vehicle, 10% registered two vehicles and 0.2% of drivers registered three vehicles, which makes up for 1,218 ridehailing vehicles that are observed in the data.

Table 5-1 Vehicle availability for household vehicles and ridehailing vehicles

	Household Vehicles		**TNC Vehicles**	
Number of vehicles	**Sample size**	**Percentage**	**Sample size**	**Percentage**
1	438	39.8%	982	89.4%

[8] Under a non-disclosure agreement (NDA), one of the TNCs provided detailed crosstabs of key driver demographics in California, including age, gender, ethnicity/race, household income, average weekly work hours, and tenure in the platform, segmented by geographic region. Since many drivers work across both platforms, I assumed no systematic differences between the two TNCs and used these crosstabs as benchmarks to generate weights for the entire sample. The information provided by the TNC was used as the control variables in the weighting technique. The use of weights largely reduces the discrepancies between the demographic distributions of the sample and that of the driver population in California.

2	448	40.8%	114	10.4%
3	107	9.7%	3	0.2%
4+	106	9.6%	---	---

Table 5-2 lists the ten most common fuel type combinations among household and ridehailing vehicles. Overall, 58.7% of drivers have only ICEV(s) as their household vehicles, while 62.2% of drivers use only ICEV(s) for ridehailing work. In contrast, 6.5% of drivers have only BEV(s) as household vehicles, compared to 13.2% who register only BEV(s) with TNCs. Among drivers who only registered a single vehicle, an ICEV was the most common fuel type, followed by HEV, BEV and PHEV. With regards to the combination of two fuel types, the ICEV-HEV combination is the most common among household vehicles, whereas the ICEV-BEV combination is the most common among ridehailing vehicles.

Table 5-2 Fuel type combinations of household and ridehailing vehicles (ten most common choices of each)

Household vehicles				**Ridehailing vehicles**			
Vehicle count	**Fuel type combinations**	**Sample size**	**Percentage**	**Vehicle count**	**Fuel type combinations**	**Sample size**	**Percentage**
1	ICEV	313	28.5%	1	ICEV	639	58.2%
2	ICEV, ICEV	233	21.2%	1	HEV	168	15.3%
2	ICEV, HEV	79	7.2%	1	BEV	133	12.1%
1	HEV	78	7.1%	2	ICEV, ICEV	43	3.9%
3	ICEV, ICEV, ICEV	61	5.6%	1	PHEV	42	3.8%
2	ICEV, BEV	47	4.3%	2	ICEV, BEV	20	1.8%
2	BEV, BEV	34	3.1%	2	BEV, BEV	12	1.1%
1	BEV	31	2.8%	2	PHEV, BEV	12	1.1%
4	ICEV, BEV	24	2.2%	2	BEV, ICEV	9	0.8%
4	ICEV, ICEV, ICEV, ICEV	22	2.0%	2	ICEV, HEV	5	0.5%

(2) Factors Influencing Ridehailing Vehicle Choice

Out of the 12 factors listed in Figure 5-1, respondents were asked to identify up to three main factors that influenced their choice of ridehailing vehicle(s), regardless of whether they obtained the vehicle(s) with or without the intention of ridehailing work. Fuel type and fuel efficiency are the common factors for choosing HEVs, PHEVs and BEVs. Another main motivation for choosing BEVs was to become eligible to provide upgraded services (e.g., Uber Comfort Electric) for higher earnings. Other motivations for ICEVs and HEVs are the vehicle size and price.

I further explore the reasons why drivers chose certain fuel types. As illustrated in Figure 5-2, saving money on fuel and maintenance, and having access to cheaper or priority parking[9], are the three main factors encouraging drivers to use an EVs (PHEVs or BEVs) for ridehailing work (Sanguinetti & Kurani, 2021). Furthermore, among PHEV drivers, the three main reasons for opting to use a PHEV instead of a BEV for ridehailing work are: a lack of charging stations in their service area, reluctance to take time away from driving to recharge, and concerns about limited driving range restricting the number of rides (see Figure 5-3). Finally, among drivers who do not drive an EV (PHEV or BEV) for ridehailing work, but have access to one at home, the fact that the vehicle is being used by some other household members is the dominant reason (see Figure 5-4).

[9] Some parking lots reserve dedicated spaces for EVs, and some municipalities waive parking fees for EVs.

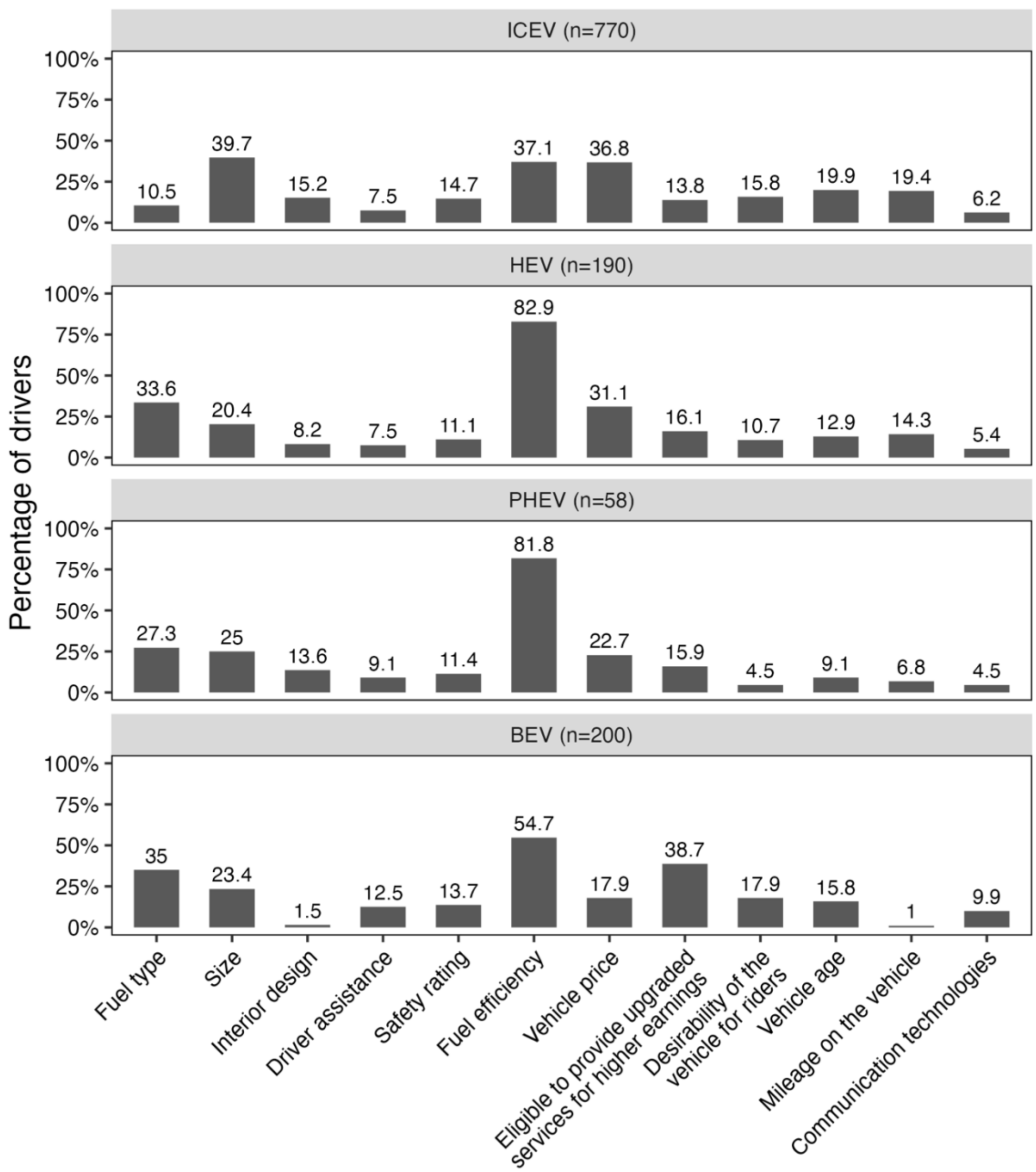


Figure 5-1 Factors influenced the ridehailing vehicle choices

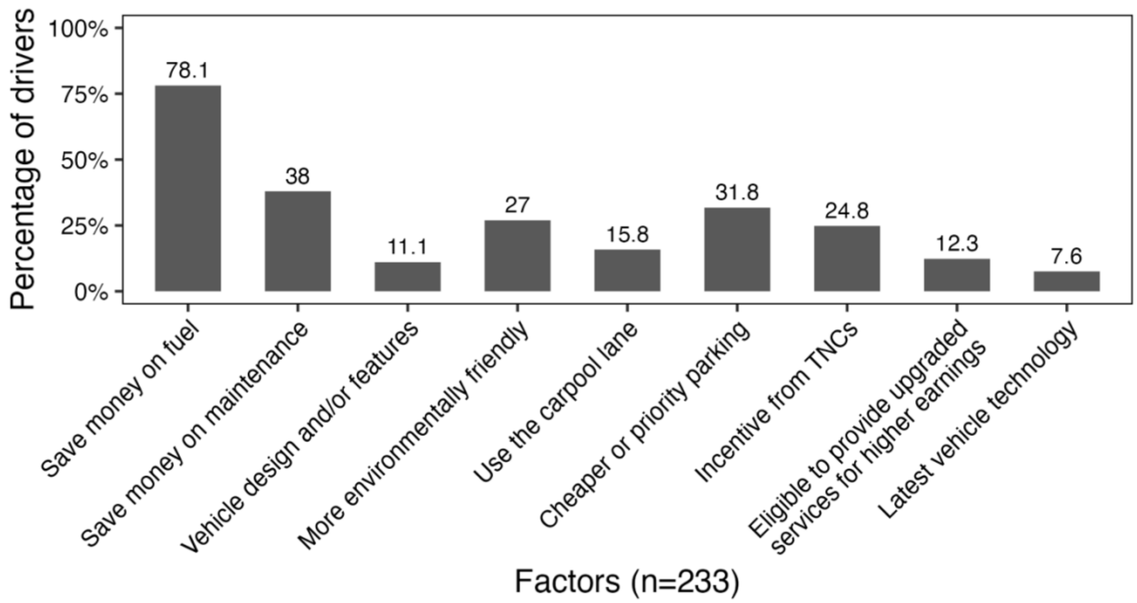


Figure 5-2 Reasons for driving an EV (BEV or PHEV) for ridehailing work

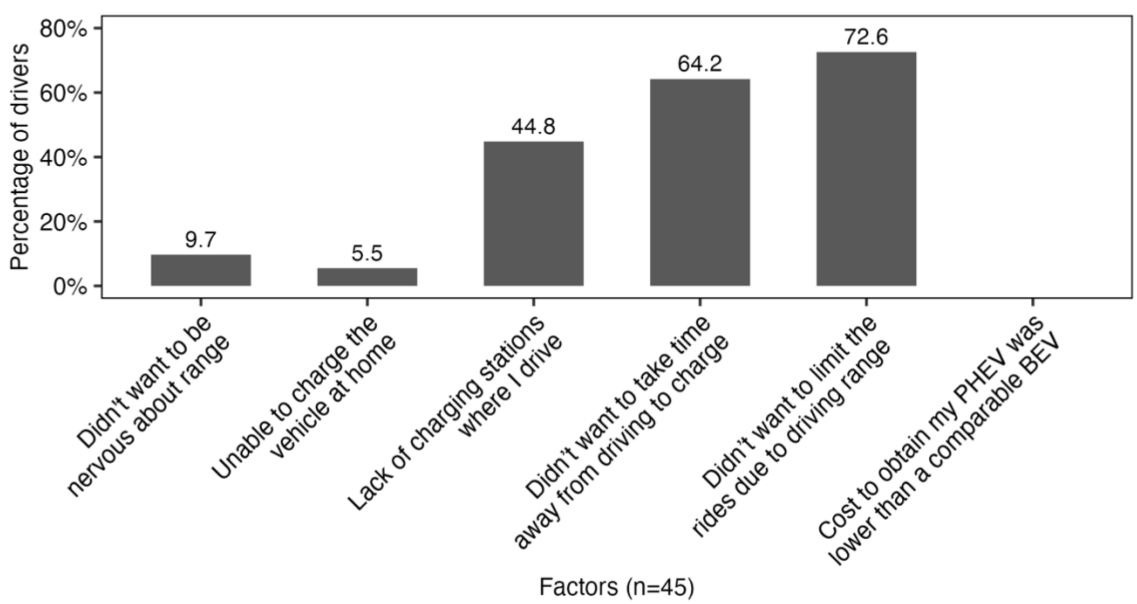


Figure 5-3 Reasons for driving a PHEV instead of a BEV despite of having access to a BEV at home

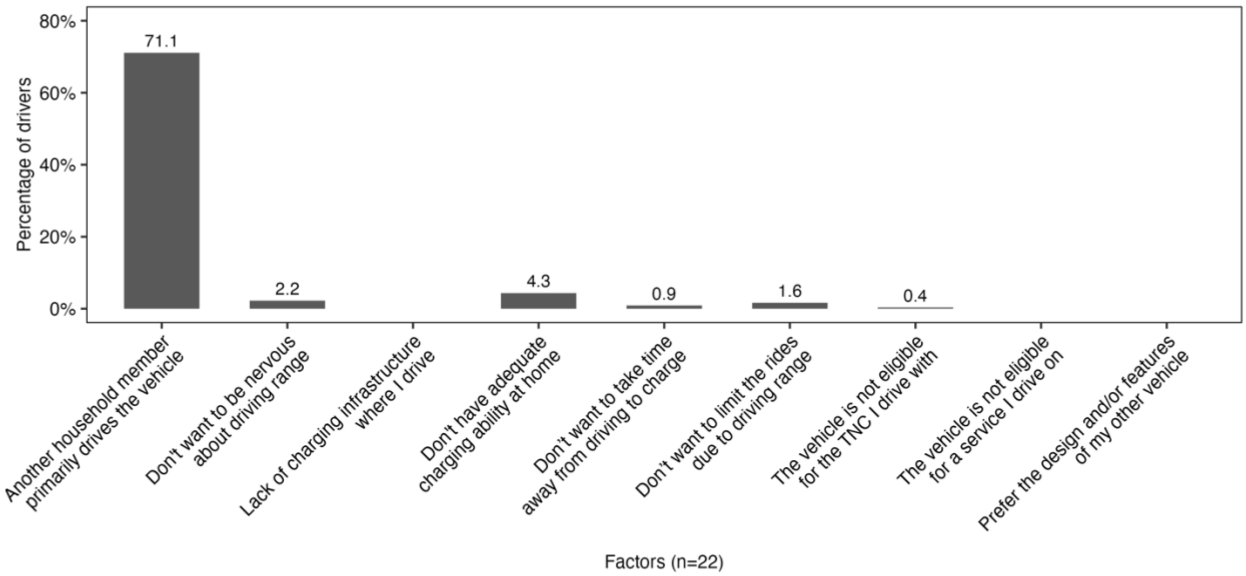
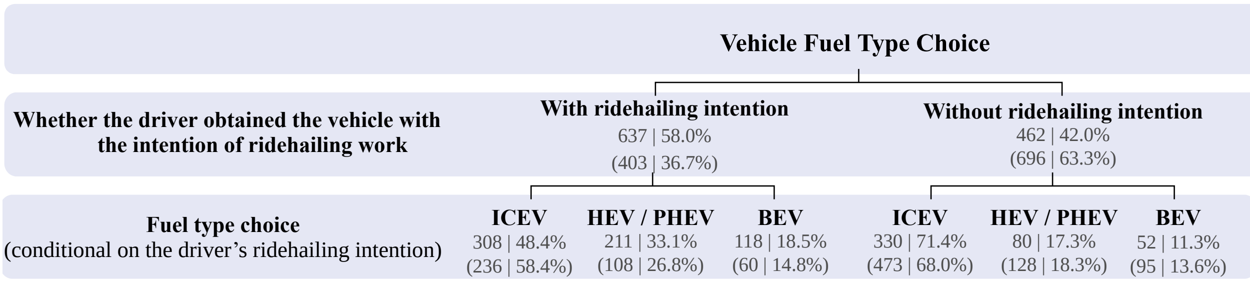


Figure 5-4 Reasons for not driving a PHEV or a BEV despite having access to one at home.

5.4.3 Dependent Variables

The focus of this study is to model drivers' fuel type choices for their ridehailing vehicles. Given that most drivers (89.4%) only registered one vehicle on the TNC platform, analyses from this point onwards will focus only on the vehicle *that serves the most ridehailing rides* from each driver.

As discussed in previous sections, a variety of factors can potentially impact drivers' choices of vehicle fuel type, including socio-demographic characteristics, personal attitudes, and the attributes of competing vehicles. However, an additional and critical aspect of this decision process is explicitly addressed in the modeling. In practice, drivers' fuel-type choice of a ridehailing vehicle is often intertwined with *whether the vehicle was obtained with the intention of ridehailing work*" (referred to as "*ridehailing intention*" hereafter for brevity) or selected from a pre-existing household fleet which was not obtained with the ridehailing intention. The decision to use a particular vehicle may be more directly influenced by the specific attributes of ridehailing work in the former case, whereas, in the latter case, it may be more closely tied to the general decision of vehicle purchase/ownership of drivers' households.



Note: The numbers and percentages in the figure represent the unweighted sample size and proportions, with weighted values shown in parentheses. I grouped hybrid HEVs and PHEVs into a category due to the low occurrence of PHEVs in the data.

Figure 5-5 *Aggregated shares of fuel type choice conditional on whether the vehicle was obtained with the intention of using it for ridehailing work*

I explicitly model drivers' ridehailing intention for several reasons. As illustrated in Figure *5-5*, thirty-seven percent of drivers in the target population obtained their vehicle with ridehailing intention, indicating that while not dominant, it is a phenomenon that cannot be overlooked. The fuel type choices are statistically different between drivers with and without ridehailing intention (p-value =0.002). Besides, such intention often hinges on various practical, financial, and personal factors. For example, among those who do not own a household vehicle, obtaining a vehicle is clearly the first step to enrolling as a ridehailing driver. Moreover, TNCs often have requirements regarding the age, size, and condition of registered vehicles. The household vehicles of some drivers may not meet these requirements, prompting them to acquire another one if they wish to drive for TNCs. Vehicles with more seating or premium features might allow drivers to offer premium services (e.g., Uber Premium, Lyft Black). Additionally, some drivers may invest in more fuel-efficient or electric vehicles for ridehailing work to lower their operational costs. Conversely drivers who only plan to drive occasionally and already have a household vehicle suitable for ridehailing work — without conflicts in usage with other household members — have less of a need to obtain an additional vehicle. Therefore, it is reasonable to hypothesize that these two groups of drivers have quite distinctive characteristics and decision-making process when it comes to fuel type choices.

5.4.4 Independent Variables and Sample Statistics

Table 5-4 provides a detailed summary of variables that will be tested in the model. The subsequent paragraphs describe how I obtained and processed those variables.

In the survey, twenty attitudinal statements related to EVs were chosen to represent five pre-defined factors based on the Theory of Planned Behavior (Ajzen, 1991; Haustein & Jensen, 2018; Kaplan et al., 2016; Zhou et al., 2021). Respondents expressed their level of agreement with each statement using a 5-point Likert scale. The confirmatory factor analysis (CFA) (see Table 5-3) confirms the following five factors related to EVs (see Rows 1-5 of Table 5-4) with adequate model fit (Tucker-Lewis Index=0.90, Comparative Fit Index=0.91 and Standardized Root Mean Squared Residual=0.06). Drivers with higher values for the *attitude* latent variable are more likely to believe that driving an EV for ridehailing offers long-term environmental benefits, greater cost savings, and increased profits. Those with higher *subjective norm* values perceive EVs as positively regarded in the ridehailing industry, with growing interest among drivers and riders who view them favorably and express greater satisfaction with EV options. Drivers scoring higher on the *perceived control* latent variable agree that EVs enable them to offer the premium services that they desire and find existing maintenance and charging facilities sufficient. Conversely, those with higher values on *perceived barriers* attitude agree that EVs are often impractical for ridehailing work due to limited range, high costs, the need for frequent charging, and the additional planning that is required. Finally, drivers with higher *effort expectancy* values agree that learning and becoming skillful at driving EVs for ridehailing work would be challenging.

Table 5-3 Results from the confirmatory factor analysis

Index	Attitudinal statements	EV Attitude	EV subjective norm	EV perceived control	EV perceived barriers	EV effort expectancy
1	Driving an electric vehicle for rideshare work would be beneficial to the environment in the long term.	0.85				
2	It is advantageous to drive an electric vehicle for rideshare work because of the low energy cost.	0.79				
3	I would increase my profits by driving an electric vehicle for my rideshare work.	0.76				
4	Driving an electric vehicle for rideshare work would eventually result in cost savings.	0.65				
5	Riders are more satisfied with electric rideshare vehicles.		0.81			
6	More riders favor electric rideshare vehicles.		0.79			
7	Electric vehicles are viewed favorably in the rideshare industry.		0.73			
8	Some people who are important to me think I should have an electric vehicle for my rideshare work.		0.58			
9	I know rideshare drivers who are considering electric vehicles.		0.47			
10	It is easy to charge an electric rideshare vehicle.			0.70		
11	The charging facilities for electric rideshare vehicles are sufficient.			0.64		
12	Maintenance facilities for electric rideshare vehicles are sufficient.			0.58		
13	I could drive for any rideshare service that I want with an electric vehicle.			0.48		
14	The need for charging makes electric vehicles very unpractical for rideshare work.				0.77	
15	The driving range of electric vehicles is too short for my rideshare work.				0.66	
16	Using an electric vehicle would require careful planning of my activities as a rideshare driver.				0.49	
17	The price of an electric vehicle for rideshare work is too high.				0.46	
18	It would be easy for me to become skillful at driving an electric vehicle for my rideshare work.					0.81
19	Learning how to drive an electric vehicle for my rideshare work would be easy for me.					0.74

Note: The optimal model used 19 out of the 20 attitudinal statements.

Rows 6-30 of Table 5-4 summarize drivers' individual and household characteristics and Rows 31-42 summarize their ridehailing vehicle profiles (e.g., own/lease/rent), as well as the location and duration of their ridehailing work.

Drivers reported perceived EV charger access in the following locations: (1) private and exclusive access at their home/garage, and (2) in public areas beyond nearby streets (Rows 43-50). Since respondents could select multiple charger types for each location, I used the highest-level chargers they reported as the final measure. Due to the rarity of direct-current fast chargers (DCFC) at home and Level 1 chargers in public areas, some charger types were aggregated for modeling purposes. The final variable includes four levels for home chargers (Level 1, Level2, available but unknown level, none) and four levels for public chargers (Level 1/Level2, DCFC, available but unknown level, none).

Drivers also reported their familiarity with, or usage of, various federal, state, and local EV-related incentives. I listed common federal and state incentives in the survey (see Figure 5-6). Drivers could also self-report additional incentives that they were aware of. As Figure 5-6 illustrates, drivers have the highest awareness of the New or Used EV Tax Credit and Clean Vehicle Rebate Project, though actual usage rates remain low. Furthermore, drivers with higher household incomes displayed greater awareness of many of these incentives. Since the survey did not ask drivers who used these incentives to specify if they applied them to their current ridehailing vehicle, there is a potential for this variable to strongly predict their BEV adoption (Du et al., 2020). To avoid this confounding factor, I decided to exclude drivers who reported using any of these incentives from modeling (n=110). To address multicollinearity issues, I grouped all incentives into two categories: federal incentives and state/local incentives. For each respondent, I then assigned the highest level of familiarity reported across all incentives within each of these two categories.

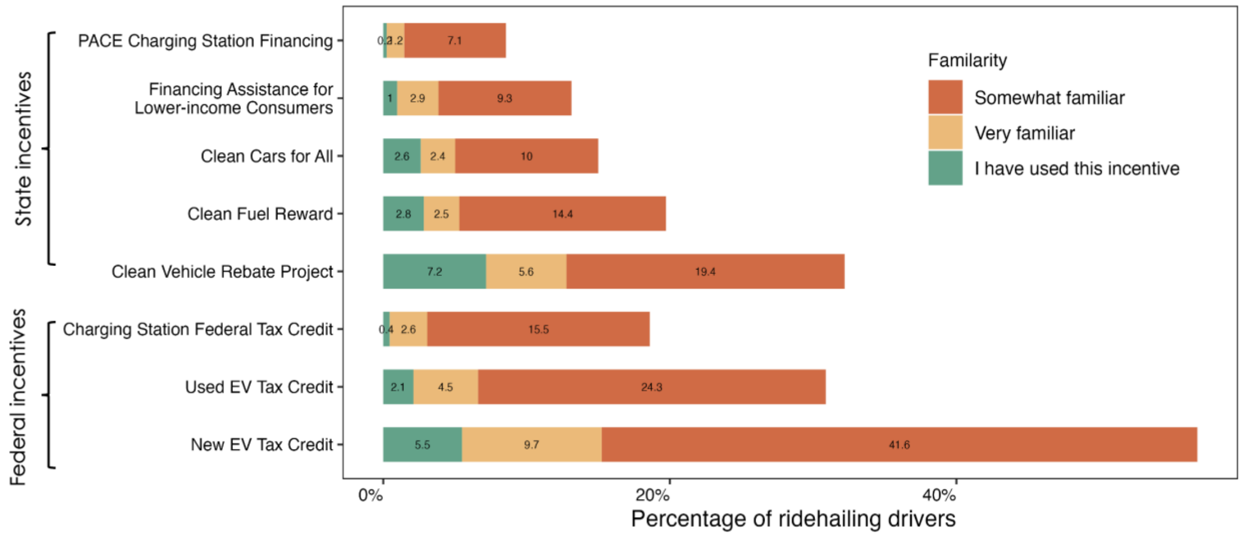


Figure 5-6 Level of familiarity with EV-related incentives among ridehailing drivers

To further enrich the dataset, I incorporated population and employment density data from the Smart Location Database prepared by the US Environmental Protection Agency (Chapman et al., 2021). These continuous density measures were then categorized into three levels, corresponding to the statewide distribution: low (0–33rd percentile), medium (34–66th percentile), and high (67–100th percentile). In addition, to capture “EV Neighborhood Effects” which reflects the potential for peer influence to lead to positive perceptions of EVs (Chakraborty et al., 2022; Iogansen et al., 2023), I collect the share of registered vehicles that are EVs among all vehicle stock within the ZIP code where each driver lives) from the US Department of Energy (2024) website.

Table 5-4 Characteristics of drivers by fuel type choices

<table>
<tr><td>A</td><td>B</td><td>C</td><td>D</td><td>E</td><td>F</td><td>G</td><td>H</td></tr>
<tr><td rowspan="2">Row Index</td><td rowspan="2">Variables</td><td rowspan="2">Categories</td><td rowspan="2">Weighted n</td><td rowspan="2">Column-wise weighted %</td><td colspan="3">Weighted row-wise % by fuel type</td></tr>
<tr><td>ICEV (708 | 64.5%)</td><td>HEV/PHEV (236 | 21.5%)</td><td>BEV (154 | 14.1%)</td></tr>
<tr><td>1</td><td rowspan="4">Latent attitudes (average factor score)</td><td>EV attitude</td><td>1099</td><td>100.0%</td><td>0.08</td><td>0.03</td><td>0.48</td></tr>
<tr><td>2</td><td>EV subjective norm</td><td>1099</td><td>100.0%</td><td>0.02</td><td>0.08</td><td>0.62</td></tr>
<tr><td>3</td><td>EV perceived control</td><td>1099</td><td>100.0%</td><td>0.06</td><td>0.03</td><td>0.57</td></tr>
<tr><td>4</td><td>EV perceived barriers</td><td>1099</td><td>100.0%</td><td>-0.05</td><td>-0.03</td><td>-0.59</td></tr>
</table>

5		EV effort expectancy	1099	100.0%	0.05	-0.04	**0.27**
6	**Age**	18-34	275	25.1%	64.0%	**24.2%**	11.8%
7		35-54	593	54.0%	65.7%	18.7%	**15.6%**
8		55+	230	21.0%	62.0%	**25.3%**	**12.6%**
9	**Gender**	Female	246	22.4%	70.9%	19.4%	9.7%
10		Male	853	77.6%	62.6%	**22.0%**	**15.3%**
11	**Race/Ethnicity**	Not Hispanic/Latino, White only	326	29.7%	64.8%	20.8%	**14.4%**
12		Not Hispanic/Latino, other race(s)	358	32.6%	66.8%	19.0%	**14.3%**
13		Hispanic/Latino, no matter what race(s)	414	37.7%	62.3%	**24.1%**	13.6%
14	**Education**	Less than Bachelor's	651	59.3%	66.2%	**22.0%**	11.8%
15		Bachelor's degree(s) or other	447	40.7%	61.9%	20.7%	**17.3%**
16	**Student status**	Non-student	991	90.2%	65.6%	20.3%	14.1%
17		Student	107	9.8%	53.8%	**32.5%**	13.7%
18	**Work status outside of ridehailing work**	No other job	230	20.9%	65.2%	19.7%	15.1%
19		Other full-time job	293	26.7%	54.5%	**28.8%**	**16.6%**
20		Other Part-time job	576	52.4%	69.3%	18.4%	12.3%
21	**Annual household income**	Below $50,000	457	41.6%	65.5%	**22.3%**	12.1%
22		$50,000 to $99,999	386	35.1%	63.9%	**25.2%**	10.9%
23		$100,000 or above	256	23.3%	63.5%	14.3%	**22.2%**
24	**Housing tenure**	Rent or provided by others	803	73.1%	67.5%	20.8%	11.7%
25		Own	295	26.9%	56.3%	**23.4%**	**20.3%**
26	**Housing type**	Multi-family house or apartment	604	55.0%	65.2%	20.5%	**14.3%**
27		Detached house	494	45.0%	63.6%	**22.6%**	13.8%
28	**Total number of household vehicles**	1	438	39.8%	73.0%	19.9%	7.1%
29		2	448	40.8%	60.7%	**24.7%**	**14.6%**
30		3 or more	213	19.4%	55.0%	17.9%	**27.1%**
31	**Ridehailing vehicle ownership**	Own	995	90.6%	64.5%	**22.1%**	13.4%
32		Lease or Rent through TNC rental program	103	9.4%	64.5%	15.6%	**19.9%**
33	**Ridehailing intention**	TNC vehicle obtained without intention of TNC work	695	63.3%	68.0%	18.3%	13.6%
34		TNC vehicle obtained with intention of TNC work	403	36.7%	58.4%	**26.8%**	**14.8%**
35	**Region of ridehailing work**	Rest of CA	219	19.9%	68.9%	18.9%	12.1%
36		MTC	190	17.3%	66.5%	**24.7%**	8.8%
37		SCAG	438	39.8%	66.2%	21.4%	12.3%
38		SACOG	41	3.7%	62.1%	**31.0%**	6.9%
39		SANDAG	211	19.2%	54.9%	19.4%	**25.7%**
40	**Ridehailing weekly work hour**	<10	685	62.3%	70.0%	17.3%	12.7%
41		10-25	344	31.3%	55.8%	**28.8%**	**15.4%**
42		>25	70	6.4%	53.6%	**26.2%**	**20.2%**
43	**Chargers at my home/garage**	None	616	56.1%	75.3%	18.9%	5.7%
44		Level 1	126	11.5%	40.3%	**35.5%**	**24.2%**

45		Level 2	178	16.2%	35.8%	16.7%	**47.5%**
46		Available but unknown le vel	178	16.2%	72.7%	**25.1%**	2.2%
47	**Chargers at public areas**	None	303	27.6%	76.7%	16.0%	7.3%
48		Level 1 or Level 2	122	11.1%	63.1%	**24.3%**	12.6%
49		DCFC	319	29.1%	46.4%	20.1%	**33.5%**
50		Available but unknown le vel	354	32.2%	70.8%	**26.4%**	2.8%
51	**Familiarity with federal EV incentives**	Not at all familiar	443	43.3%	75.2%	**22.0%**	2.7%
52		Somewhat familiar	453	44.3%	66.1%	**22.3%**	11.5%
53		Very familiar	127	12.4%	52.7%	11.3%	**36.0%**
54	**Familiarity with state/local EV incentives**	Not at all familiar	706	70.1%	70.4%	**21.9%**	7.6%
55		Somewhat familiar	216	21.4%	72.4%	16.8%	10.9%
56		Very familiar	85	8.4%	53.0%	12.0%	**35.0%**
57	**Population density at residential location**	Low	389	35.4%	65.5%	**20.2%**	14.3%
58		Medium	371	33.8%	72.5%	16.0%	11.4%
59		High	339	30.8%	54.5%	**28.9%**	**16.6%**
60	**Employment density at residential location**	Low	302	27.5%	71.1%	13.0%	**16.0%**
61		Medium	383	34.8%	61.3%	**25.1%**	13.6%
62		High	414	37.7%	62.6%	**24.3%**	13.1%
63	**EV Neighborhood effect**	EV share within residential ZIP code area	1099	100.0%	9.4%	10.1%	**11.0%**

Note: In the table, bolded values indicate numbers exceeding the weighted sample average for HEVs/PHEVs or BEVs in their respective columns. I hypotheses that drivers with these specific characteristics are more likely to adopt either HEVs/PHEVs or BEVs, compared to their counterparts.

5.4.5 Modeling Method

I estimate an integrated choice and latent variable (ICLV) model (Abou-Zeid & Ben-Akiva, 2014b; Ben-Akiva et al., 2002) to explain (1) the relationship between drivers' observable characteristics and latent attitudes towards EVs, and (2) the relationship between latent attitudes and other determinants and fuel type choices (see Figure 5-7). The model was estimated in R package Apollo (Hess & Palma, 2019) using the Bunch et al. (1993) maximum likelihood estimation algorithm.

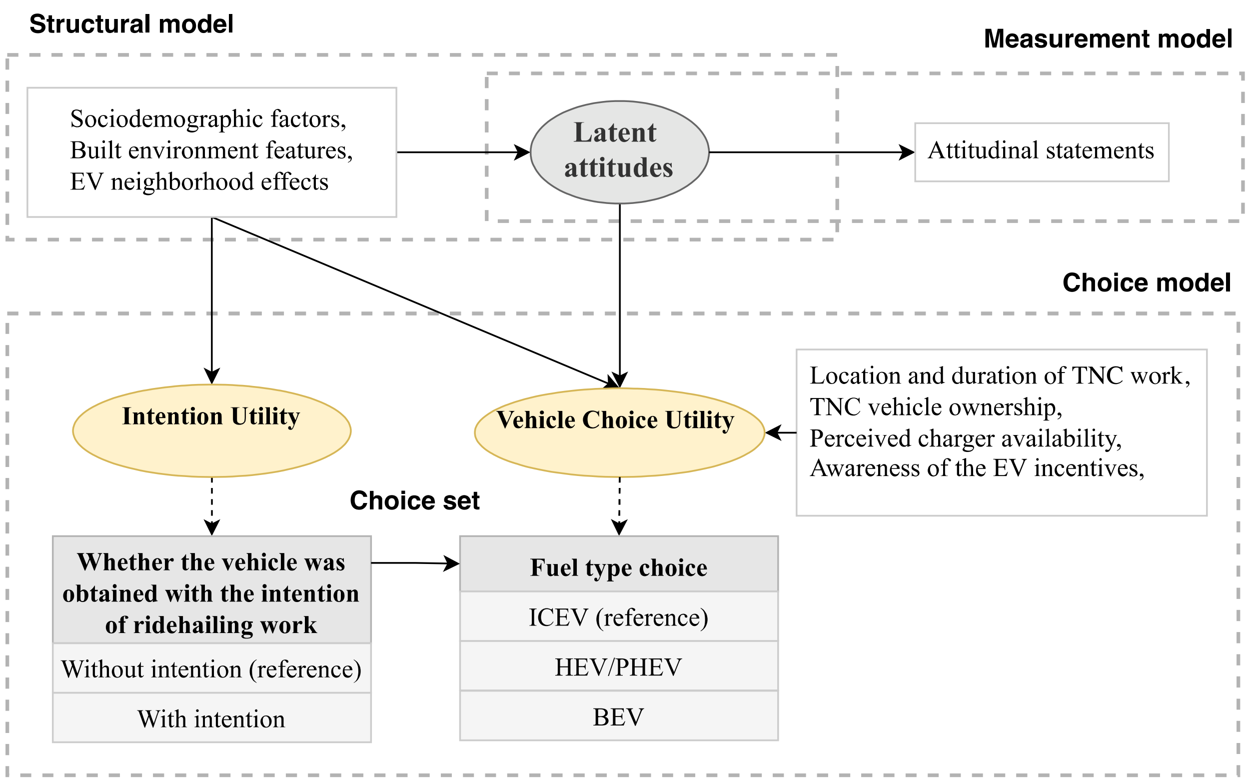


Figure 5-7 ICLV model framework

The ICLV model consists of a latent variable model and choice model. The measurement model (Eq. 1) identifies the relationship between attitudinal statements and latent attitudinal factors. The number of factors and specifications of the equations are informed by the initial confirmatory factor analysis (CFA). The structural model (Eq. 2) explores the relationship between observable characteristics (e.g., socio-demographics) and latent factors, which would otherwise be represented as “unobservable heterogeneity” using standard discrete choice modeling approaches.

$$i_n = Dx_n^* + \eta_n \,,\ \eta_n \sim N(0, \Psi) \qquad \text{(Eq. 1)}$$

where i_n is a vector of individual n’s response to attitudinal statements; D is a matrix of factor loading to be estimated; x_n^* is a vector of latent variables for individual n; and η_n is the error term with a normal distribution with a zero mean;

$$x_n^* = As_n + v_n \text{ , } v_n \sim N(0, \Phi) \qquad \text{(Eq. 2)}$$

where s_n is vector of observable socio-demographic features; A is a matrix of regression coefficients whose values reflect the influence of socio-demographic features and latent factors; v_n is the measurement error with a normal distribution with a zero mean;

Regarding the choice model, the factors influencing ridehailing intention, and fuel type choices were examined using a conditional model with one binary logit (Eq.3.1) and two multinomial logit (MNL) (Eq. 3.2) sub-models[10]. The binary choice of obtaining a vehicle with the intention of using it for ridehailing is determined by the following utilities:

$$u_{ni}^{ri} = \begin{cases} B_n^{ri} s_n^{ri} + \epsilon_{n1}^{ri} \\ 0 + \epsilon_{n0}^{ri} \end{cases} \text{, } \epsilon_{ni}^{ri} \sim i.i.d. \text{ Gumbel for } i = 1,0 \quad \text{(Eq. 3.1)}$$

where u_{ni}^{ri} is the individual *n*'s utility for ridehailing intention ('ri') alternative *i* (*i* = 1 for 'yes', *i* = 0 for 'no'); B_n^{ri} is a vector of coefficients for individual *n*; s_n^{ri} is row vector of observable socio-demographic features; ϵ_{ni}^{ri} is the random disturbances for ridehailing intention alternative *i* corresponding to the unobserved component of utility that are assumed to be independent and identically distributed and follow the *i.i.d.* Gumbel distribution.

There are two MNL models for fuel ('f') choice *j*, conditional on the outcome of the ridehailing intention *i*, where utilities are given by:

$$u_{nj|i}^f = B_{nj|i}^f s_n^f + \Gamma_{nj|i}^f x_n^* + \epsilon_{nj|i}^f \text{ , } \epsilon_{nj|i}^f \sim \text{i. i. d. Gumbel} \quad \text{(Eq. 3.2)}$$

where $u_{nj|i}^f$ is the individual *n*'s utility of fuel type *j* (*j*=2 for 'BEV', *j*=1 for 'HEV/PHEV', *j*=0 for 'ICEV'), conditional on ridehailing intention i; $B_{nj|i}^f$ is a vector of coefficients; s_n^f is a row vector of

[10] I have also tried several nesting structures with "intention" as the upper nest and "fuel type choice" as the lower nest, they were not ultimately supported by the data as the parameter θ which captures the correlation between alternatives within the same nest is beyond commonly accepted range (between 0 and 1), which is typical required to ensure meaningful interpretation and maintain the nested structure's validity. For the current two MNL models, I applied the Hausman-McFadden test (Hausman & McFadden, 1984) and determined that Independence of Irrelevant Alternatives (IIA) assumption (Ray, 1973) was not violated in either case.

observable socio-demographic features; $\Gamma_{nj|i}^{f}$ is a row vector coefficients whose values reflect the influence of each latent factor for the relevant choice situation; and $\epsilon_{nj|i}^{f}$ is an of the *i.i.d* Gumbel random disturbance. Note that in these MNL models *j* = ICEV is the base alternative so that $\mathrm{B}_{nj|i}^{f} \equiv 0$ for *j* = ICEV and *i*= 0,1.

The choice models assume utility maximization, as shown in equations 4.1 and 4.2.

$$y_{ni}^{ri} = \begin{cases} 1, \text{if } u_{ni}^{ri} \geq u_{ni'}^{ri}, \forall i' \\ 0, \text{ otherwise} \end{cases} \qquad \text{(Eq. 4.1)}$$

$$y_{nj|i}^{f} = \begin{cases} 1, \text{if } \mathrm{u}_{nj|i}^{f} \geq \mathrm{u}_{nj'|i}^{f}, \forall \mathrm{j}' \\ 0, \text{ otherwise} \end{cases} \qquad \text{(Eq. 4.2)}$$

The probability of driver n obtaining the vehicle with/without intention and fuel type choice is given by:

$$\mathrm{P_n}\left(y_{ni}^{ri}, y_{nj|i}^{f}\right) = \mathrm{P_n}\left(y_{ni}^{ri}\right) * \mathrm{P_n}\left(y_{nj|i}^{f}\right) \quad \text{(Eq. 4.3)}$$

where $\mathrm{P}\left(y_{ni}^{ri}\right)$ is the probability of displaying ridehailing intention *i*; $\mathrm{P}\left(y_{nj|i}^{f}\right)$ is the probability of fuel type choice *j* conditional on ridehailing intention *i*.

5.5 Results and Discussions

5.5.1 Latent Variable Model

Three latent factors were found to have a statistically significant impact on vehicle fuel type choices: *attitude*, *subjective norm*, and *perceived barriers*. Table 5-5 displays the coefficients from the measurement equations, indicating the relationships between each attitudinal statement and its corresponding latent attitudinal factor.

Table 5-6 shows the estimated coefficients from the structural equations, confirming associations between ridehailing drivers' observable characteristics and their attitudes towards EVs. This also suggests that there are some indirect effects of socio-demographic characteristics on fuel type choices through their impacts on attitudes.

EV attitude: Younger drivers, residents of detached homes, and those living in more highly populated regions tend to have more positive attitudes towards EVs, viewing them as environmentally friendly and profitable for ridehailing work. This aligns with previous research showing that younger individuals are more environmentally conscious (Iogansen et al., 2023), homeowners benefit more from home charging, and residents in high-density areas have better access to public charging (Zou et al., 2020).

EV subjective norm: Younger drivers are more likely to view EVs as part of the social norm, consistent with studies showing higher EV interest among younger population (Chen et al., 2020). Drivers residing in areas with a higher share of EVs demonstrate greater interest in EVs, reflecting a possible "neighborhood effect".

EV perceived barriers: Hispanic drivers are more likely to perceive barriers to EV adoption, potentially due to socioeconomic challenges that amplify the costs of EV ownership and charging facilities. In contrast, drivers living in areas with greater employment density perceive fewer barriers, likely due to better access to charging infrastructures. Interestingly, higher-educated drivers report greater perceived barriers, potentially due to concerns about time management, as stated in the attitudinal statement: "Using an EV would require careful planning of my activities as a rideshare driver". More highly educated individuals may place higher value on time, making the additional time for charging less financially viable for them.

Table 5-5 Final estimates of the measurement model

		Latent Attitudinal Factors					
		EV attitude		**EV subjective norm**		**EV perceived barriers**	
Index	**Attitudinal statements**	Coef.[1]	t-stat.[1]	Coef.	t-stat.	Coef.	t-stat.
1	Driving an electric vehicle for rideshare work would be beneficial to the environment in the long term.	0.75	14.32				
2	It is advantageous to drive an electric vehicle for rideshare work because of the low energy cost.	0.75	15.98				
3	I would increase my profits by driving an electric vehicle for my rideshare work.	0.74	15.02				
4	Driving an electric vehicle for rideshare work would eventually result in cost savings.	0.70	12.44				
5	Riders are more satisfied with electric rideshare vehicles.			0.93	20.31		
6	More riders favor electric rideshare vehicles.			0.91	20.87		
7	Electric vehicles are viewed favorably in the rideshare industry.			0.83	18.71		
8	Some people who are important to me think I should have an electric vehicle for my rideshare work.			0.71	15.78		
9	I know rideshare drivers who are considering electric vehicles.			0.55	11.44		
10	The need for charging makes electric vehicles very unpractical for rideshare work.					0.75	14.34
11	The driving range of electric vehicles is too short for my rideshare work.					0.78	14.18
12	Using an electric vehicle would require careful planning of my activities as a rideshare driver.					0.52	10.55
13	The price of an electric vehicle for rideshare work is too high.					0.43	8.48

Note: Statistics in the table represent coefficients and t-statistics. They are all statistically significant at the 99% confidence level (p-value <0.01).

Table 5-6 Final estimates of the structural model

Variables	**Categories**	**Latent Factors**								
		EV attitude			**EV subjective norm**			**EV perceived barriers**		
		Coef.[1]	**t-stat.**[1]	**p-val.**[1]	**Coef.**	**t-stat.**	**p-val.**	**Coef.**	**t-stat.**	**p-val.**
Age group (ref: 18-34)	35-54	-0.31	-3.18	<0.01	-0.28	-3.38	0.00			
	55 or over	-0.34	-3.08	<0.01	-0.28	-3.29	0.00			
Race/Ethnicity (ref: non-Hispanic, White only)	Non-Hispanic, other race(s)							0.07	0.65	0.51
	Hispanic, regardless of race(s)							0.17	1.57	0.10
Education level (ref: below Bachelor)	Bachelor's degree or higher							0.25	2.90	<0.01
Housing type (ref: multi-family house or apartment)	Stand-alone house	0.22	2.04	0.04						
EV share within residential ZIP code area					3.90	2.77	0.01			
Population density (ref: low or medium)[2]	High	0.26	2.38	0.02						
Employment density (ref: low or medium)[2]	High							-0.28	-3.46	<0.01

Notes:
1. Statistics in the table represent coefficients, t-statistics, and p-values. At least one level of each categorical variable is statistically significant at or above the 90% confidence level.
2. For the population and employment density variables, statistically significant differences in the parameter values corresponding to the low and medium levels were not observed, so I aggregated them into one category.

5.5.2 Choice Model

Table 5-7 and Table 5-8 summarize the impacts of factors including socio-demographic characteristics, latent attitudinal factors, perceived charger access and familiarity with incentives on "ridehailing intention" and vehicle fuel type choices, respectively. The final specification of choice model provides insights to the three key research questions.

Older drivers, those without jobs other than ridehailing work, and renters of apartments or multi-family housing are more likely to have obtained a vehicle with the intention of using it for ridehailing work. The following paragraphs outline the factors influencing vehicle fuel type choices for these two driver groups: those with without the ridehailing intention.

Starting with attitudes, for drivers with ridehailing intention, a more positive *EV attitude* increases the likelihood of adopting BEVs over ICEVs. However, this attitude reduces the probability of choosing a HEV/PHEV. These suggest that drivers perceive EVs as more environmentally friendly and cost-effective (Zhou et al., 2021), while holding the opposite views toward HEVs or PHEVs. HEVs rely entirely on gasoline, while PHEVs require careful planning to balance the consumption of gas and electric mileage. Moreover, both typically require higher upfront purchase costs. Unsurprisingly, EV-related benefits are only statistically significant for those with ridehailing intention, as they are far more likely to be full-time drivers (12.4%) compared to their counterparts (3.2%). Next, *EV favorable subjective norm* is linked to a higher likelihood of adopting all non-ICEV options, though the effect is not statistically significant for HEVs/PHEVs among drivers without ridehailing intention. Finally, within expectations, *EV perceived barriers* deter BEV adoption, regardless of drivers' intention. These findings are consistent with prior studies (Kaplan et al., 2016) and suggest that perceived values and risks can jointly affect drivers' fuel type decisions (Wood & Scheer, 1996).

Regarding socio-demographic characteristics, their direct effects on fuel type choices are relatively weak once their indirect effects, mediated through attitudes, are accounted for. Among drivers with ridehailing intention, younger drivers are more inclined to adopt non-ICEVs (Chen et al., 2020), and non-Hispanic White-only drivers are more likely to adopt BEVs. Within those without ridehailing intention, student drivers are more likely to adopt BEVs. Moreover, the EV neighborhood effect significantly increases the likelihood of HEV/PHEV adoption within this driver group, while for all other cases, its impact is realized through the *EV subjective norm* latent attitude.

In terms of ridehailing vehicle ownership, vehicles leased or rented through TNC rental programs are more likely to be BEVs among drivers with ridehailing intention, even though both ICEVs and EVs are available in these rental options.

Having (perceived) access to home chargers or public chargers promotes BEV adoption; however, the impact of home chargers was only statistically significant for drivers without ridehailing intention, while the impacts of public chargers were only statistically significant among those with ridehailing intention. This distinction makes sense, as vehicles in the former category often also serve personal travel needs and are potentially used by multiple household members, making home chargers much more convenient. Conversely, vehicles in the latter category are more likely to be used primarily for ridehailing work, where drivers have a greater need to recharge during shifts in public areas. This result could also be related to the impact of renting one's residence on the probability of displaying ridehailing intention.

Finally, regarding EV incentives and supporting programs, federal incentives have a statistically significant and positive impact on vehicle fuel type choices. However, a similar impact was not observed for state/local other incentives. Notably, the impact of federal incentives on drivers' fuel type choices varies depending on their level of familiarity with these incentives (e.g., somewhat familiar vs. very familiar).

Table 5-7 Final estimates of the "Intention" model

Variables	Categories	"Intention" Model With the intention of ridehailing work (ref: without the intention) Coef.	t-stat.	p-val.
(Intercept)				
Age group (ref: 18-34)	35-54	0.80	5.75	<0.01
	55 or over	1.08	6.97	<0.01
Work status outside of ridehailing work (ref: no other job)	Full-time	-0.02	-0.16	0.87
	Part-time	-0.76	-4.81	<0.01
Housing tenure (ref: Rent or provided by others)	Own	-0.46	-2.83	0.00
Housing type (ref: multi-family house or apartment)	Detached house	-0.25	-1.81	0.07
# of observation				989 (No intention: With intention =413:576)
LL (0)				-685.52
LL (Final model)				-640.42

Notes:
1. Statistics in the table represent coefficients, t-statistics, and p-values.
2. An empty cell indicates that its corresponding variable is tested for that part of model but was not statistically significant above 90% confidence interval (i.e., p-value <0.1), and was thus removed from the final model specification.

Table 5-8 Final estimates of the "fuel type choice" model

		"Fuel Type Choice" Model											
		Conditional on "with the intention of ridehailing work" (ref: ICEV)						Conditional on " without the intention of ridehailing work" (ref: ICEV)					
Variables	**Categories**	**HEV / PHEV**			**BEV**			**HEV / PHEV**			**BEV**		
		Coef.	**t-stat.**	**p-val.**	**Coef.**	**t-stat.**	**p-val.**	**Coef.**	**t-stat.**	**p-val.**	**Coef.**	**t-stat.**	**p-val.**
(Intercept)								-1.99	-5.97	<0.01	-7.00	-7.63	<0.01
Latent attitudes	EV positive attitudes	-0.42	-2.98	0.01	0.58	3.16	<0.01						
	EV favorable subjective norms	0.50	3.18	<0.01	1.02	3.95	<0.01				0.51	1.68	0.09
	EV perceived barriers				-0.79	-3.46	<0.01				-1.17	-3.16	<0.01
Age group (ref: 18-34)	35-54	-0.80	-5.06	<0.01	-2.53	-6.66	<0.01						
	55 or over	-0.56	-3.26	<0.01	-2.75	-6.90	<0.01						
Ethnicity/race (ref: non-Hispanic, White only)	Non-Hispanic, other race(s)				-1.25	-3.05	<0.01						
	Hispanic, regardless of race(s)				-1.15	-2.95	<0.01						
Student status (ref: non-student)	Student										1.89	2.47	0.01
EV neighborhood effect	EV share within residential ZIP code area							6.62	2.33	0.02			
Ridehailing vehicle ownership (ref: own)	Lease or rent through TNC rental program				2.65	6.44	<0.01						
Access to home chargers (ref: not available)	Level 1	0.68	2.23	0.03							2.52	3.00	<0.01
	Level 2	0.34	1.28	0.20							3.04	3.91	<0.01
	Available, but do not know the level[3]	0.28	1.05	0.30							---	---	---
Access to public chargers (ref: not available)	Level 1 or Level 2				-0.40	-0.74	0.46						
	DC fast charger				1.10	3.28	0.01						
	Available, but do not know the level				-2.23	-3.18	<0.01						

Federal EV incentives							
(ref: not at all familiar)	Somewhat familiar	0.08	0.21	0.83	1.87	2.64	<0.01
	Very familiar	1.13	2.47	0.01	2.55	1.87	<0.01
# of observation				576 (ICEV: HEV/PHEV: BEV= 301: 198: 77)			413 (ICEV: HEV/PHEV: BEV= 320: 67: 26)
LL (0)				-453.73			-632.80
LL (Final model)				-246.67			-477.48

Notes:

1. Statistics in the table represent coefficients, t-statistics, and p-values.
2. An empty cell indicates that its corresponding variable is tested for that part of model but was not statistically significant above 90% confidence interval (i.e., p-value <0.1), and was thus removed from the final model specification. Only statistically significant variables in one of the sub-models are shown in the table.
3. Among drivers who obtained their vehicle without the intention of using it for TNC work, no one reported "Available, but don't know the level" for home/garage charger, therefore, this level does not have coefficient.

5.5.3 Average Treatment Effects

The ICLV model offers valuable insights into how various factors impact fuel type choices. However, interpreting the magnitude of these effects directly from model coefficients can be challenging, especially when translating findings into actionable policy recommendations. Therefore, I calculate Average Treatment Effects (ATEs) (Heckman & Vytlacil, 2000) to quantify the impact of specific variables by measuring how the average predicted probability of each outcome changes when a particular variable shifts from one state to another, while keeping all other factors constant. In principle, the ATE can be calculated for any variable included in the final model. In this study, I focus on *charger availability* and *familiarity with federal incentives*, both of which are shown to be associated with BEV adoption and are particularly relevant for policymakers, utility providers, and TNCs.

Table 5-9 outlines the intervention framework, segmented by objectives, target groups, baseline conditions, methods, and levels (ranging from weak to full intervention). Drivers can be treated according to different intervention scenarios (I1to I4), with I0 representing the baseline or current scenario. I then apply the estimated ICLV model to compute the probability of each choice alternative being chosen by each treated driver across intervention states (I0-I4). Finally, the ATE is determined by the difference in average predicted probability between states I1- I4 and state I0.

Figure 5-8 illustrates key findings, showing that the BEV adoption rates increase with improvements in perceived charger availability and increased familiarity with incentives. In addition, the share of ICEVs in the ridehailing fleet declines to a greater extent than the share of HEVs/PHEVs under these interventions. However, the impacts vary based on the drivers' ridehailing intention and the intervention types. Expanding access to public DCFC chargers has a stronger influence on BEV adoption than home chargers. For federal incentives, the effect is notably greater among drivers with ridehailing intention, achieving a 10.0 percentage point (p.p.) rise in BEV share under full intervention, the highest observed impact across scenarios.

Table 5-9 Policy interventions aiming to improve charger availability and incentive familiarity

Intervention objectives [1]	**Improving the availability of public chargers**	**Improving the availability of home chargers**	**Increasing familiarity with federal incentives**	
Intervention recipients [1]	Among drivers obtaining vehicles **with** the intention of ridehailing work (n=576)	Among drivers obtaining vehicles **without** the intention of ridehailing work (n=413)	Among drivers obtaining vehicles **with** the intention of ridehailing work (n=576)	Among drivers obtaining vehicles **without** the intention of ridehailing work (n=413)
Baseline conditions (I0)	"None": 26.3% "Level 1 or Level2": 10.7% **"DCFC": 25.8%** "Available but unknown level:"37.1% [2]	"None": 54.9% "Level 1": 11.4% **"Level 2": 15.2%** "Available but unknown level": 18.4% [2]	"Not at all familiar": 45.4% "Somewhat familiar": 44.8% **"Very familiar": 9.8%**	"Not at all familiar": 44.1% "Somewhat familiar": 43.7% **"Very familiar": 12.3%**
Intervention methods	Transition X% of drivers who indicated "None" or "Level 1 or Level 2" to "DCFC"	Transition X% of drivers who indicated "None" or "Level 1" to "Level 2"	Transition X% of drivers who indicated "not at all familiar" or "somewhat familiar" to "very familiar"	
Levels of intervention	**Weaker intervention (I1):** Transition **25%** of drivers [3] **Medium intervention (I2):** Transition **50%** of drivers [3] **Stronger intervention (I3):** Transition **75%** of drivers [3] **Full intervention (I4):** Transition **100%** of drivers			

Notes:
1. Intervention objectives and recipients were selected only when the variables had a statistically significant and positive impact on BEV adoption for certain driver groups, based on the ICLV model results.
2. Drivers who indicated "Available but unknown level" are not considered in the policy interventions, due to a lack of information, but that is not to say more thought should not be allocated towards improving their awareness.
3. For I1 to I3, I took the ATE among 500 random draws of 25%, 50% and 75% of drivers from the corresponding driver groups.

	Improving the availability of **public chargers** ("None" / "L1/L2" to "DCFC")			Improving the availability of **home chargers** ("None" / " L1" to "L2")		
	Drivers **with** the ridehailing intention			Drivers **without** the ridehailing intention		
	ICEV	HEV/PHEV	BEV	ICEV	HEV/PHEV	BEV
I0 (No intervention): original market share in %	*48.4*	*33.1*	*18.5*	*71.4*	*17.3*	*11.3*
I1 (Transition 25 of drivers): p.p. change	-0.8	-0.6	1.5	-0.8	-0.2	1.0
I2 (Transition 50 of drivers): p.p. change	-1.6	-1.3	2.9	-1.7	-0.4	2.1
I3 (Transition 75 of drivers): p.p. change	-2.5	-1.9	4.3	-2.5	-0.6	3.1
I4 (Transition 100 of drivers): p.p. change	-3.3	-2.5	5.7	-3.3	-0.7	4.0

	Increasing familiarity with **federal incentives** ("Not familiar" / "Somewhat familiar" to "Very familiar")					
	Drivers **with** the ridehailing intention			Drivers **without** the ridehailing intention		
	ICEV	HEV/PHEV	BEV	ICEV	HEV/PHEV	BEV
I0 (No intervention): original market share in %	*48.4*	*33.1*	*18.5*	*71.4*	*17.3*	*11.3*
I1 (Transition 25 of drivers): p.p. change	-1.4	-1.1	2.5	-0.6	-0.1	0.7
I2 (Transition 50 of drivers): p.p. change	-2.7	-2.1	4.9	-1.4	-0.3	1.7
I3 (Transition 75 of drivers): p.p. change	-4.2	-3.2	7.4	-2.0	-0.4	2.5
I4 (Transition 100 of drivers): p.p. change	-5.7	-4.3	10.0	-2.7	-0.6	3.3

Note: p.p. stands for percentage point.

Figure 5-8 Average treatment effects of charging infrastructure and federal incentives

5.6 Conclusion

This paper investigates the motivations and barriers to electrification in the ridehailing sector, using a sample of ridehailing drivers in California. Through descriptive analyses and an ICLV model, I explore the factors impacting fuel type choices across different driver groups.

Fuel efficiency is the most frequently cited factor impacting drivers' choice of ridehailing vehicles, with fuel cost savings being the primary motivation for current EV drivers. Given that ridehailing drivers are often more profit-driven, with over 20% relying on ridehailing work as their sole income (see rows 18-20 in Table 5-4), it is crucial to ensure that electrification is economically viable for all drivers.

The factors impacting vehicle fuel type choices differ notably between drivers who obtained their vehicles with and without the intention of using them for ridehailing work. Those with ridehailing intentions often represent socioeconomically disadvantaged groups, such as older individuals, renters in multi-family dwellings, and those relying solely on ridehailing as their source of income. Their acquisition of a vehicle may have been motivated by a lack access to a household vehicle, found their existing vehicles unsuitable for TNC requirements, preferred a vehicle that qualifies them for higher-revenue services, or seek to benefit from financial incentives tied to acquiring a dedicated vehicle for ridehailing work. Understanding the vehicle choice decisions of both current and prospective drivers is critical for policymakers and TNCs to develop targeted programs that address their respective needs.

Attitudes and perceptions toward EVs play a significant role in BEV adoption among ridehailing drivers. Educational programs are essential to improve drivers' *attitudes* towards EVs (e.g., promoting their environmental and financial benefits), foster a *favorable subjective norm* of EVs (e.g., increasing drivers' awareness of the growing presence of EVs in their communities and among their peers), and reduce *perceived barriers* (e.g., highlighting that EVs are already capable of handling ridehailing driving cycles and are becoming increasingly cost-competitive with ICEVs). Providing drivers with opportunities to try using EVs and to learn from the experiences of drivers that are currently using EVs for ridehailing work can help improve the perception of EVs.

The impacts of drivers' personal and household characteristics on fuel type choices are primarily mediated through their attitudes. Nevertheless, I found that being younger and non-Hispanic White directly associated with higher likelihood of adopting BEVs among drivers with the ridehailing intention. EV outreach programs should therefore target older drivers (who may be less tech-savvy) and those from communities of color.

Most drivers drive either occasionally (62.3%) or on a part-time basis (31.3%), with only 6.4% driving full-time. Therefore, many ridehailing vehicles likely also serve the daily mobility needs of drivers and their household members. This highlights the importance of ensuring the availability of suitable EVs in the market (e.g., with long-range capabilities) and adequate charging infrastructure to support both ridehailing operations and personal use.

Currently, more than half (56.1%) of drivers do not have access to home/garage chargers and more than a quarter (27.6%) do not have access to public chargers. There are also significant disparities in charger access across race, income, and residential location. Furthermore, DCFC stations are often not strategically located near areas of high ridehailing demand. For instance, Kan et al. (2022) found that the distribution of charging stations tends to align with highways rather than central business districts or residential areas where ridehailing activities are most concentrated. This mismatch forces drivers to make detours for recharging, reducing earnings and increasing deadheading miles (i.e., driving without a passenger). Addressing these challenges requires promoting Level 2 charging in residential areas through collaboration among property owners, city governments, and TNCs. In the meantime, strategies such as offering discounted charging rates for ridehailing drivers or establishing dedicated charging stations exclusively for ridehailing fleets in high-demand public areas (Hunt & McKearnan, 2020) could be effective. The findings indicate that home chargers are more crucial for drivers without ridehailing intention (who typically drive occasionally or part-time), while public chargers are more essential for those with ridehailing intention (who often drive full-time). I estimated that the BEV share could increase by 4.0 percentage points (p.p.) if 100% of drivers without ridehailing intention have access to Level 2 home chargers, and by 5.7 p.p. increase if 100% of drivers with ridehailing intention have access to DCFC public chargers. Therefore, although increasing charger density both at home and in public areas reduces range anxiety, TNCs and utility providers can prioritize specific types of chargers in targeted locations for different driver groups to maximize cost-effectiveness.

The presence of incentives— and drivers' familiarity with them — significantly impact their likelihood of adopting BEVs. Currently, 43.3% and 70.1% of drivers are not at all familiar with any federal and state/local incentives, respectively, highlighting large untapped opportunities for increasing awareness and utilization. Moreover, drivers from low-income households have lower awareness of these incentives compared to those from high-income households, which appears to conflict with the initial objective of these incentive programs to support drivers from low-income households. Governments need more effective strategies to reach disadvantaged groups and may need to reconsider the eligibility criteria for these incentives. If 100% of drivers become very familiar with the federal incentives, the BEV share could increase by 10.0 p.p. among those with ridehailing intention and by 3.3 p.p. among those without ridehailing intention. Vehicles leased or rented through TNC rental programs (e.g., Hertz, Getaround rideshare program) are more likely to be BEVs. These programs provide TNC drivers with easy, flexible, and affordable access to a vehicle, without the burdens of maintenance, insurance and so forth. (Uber, 2024). This offers drivers an EV experience without the commitment of a purchase, potentially facilitating a smoother transition to EVs in the long run. However, it is worth noting that governments have been reducing EV incentives in recent years, and ultimately, the EV industry must evolve to be more market-oriented than policy-dependent. Similarly, TNCs have indicated that their EV rental programs are just a near-term strategy, and that EV purchases by ridehailing drivers will be critical to achieving electrification targets (Hunt & McKearnan, 2020).

Finally, it is important to acknowledge some limitations of this study. Most of the data used in this study reflects drivers' characteristics at the time of the survey, which may not fully align with their status when they initially registered their vehicles on the TNC platform. I assumed consistency between these two points in time and analyzed the relationships between drivers' current characteristics (including attitudes) and their vehicle choices made sometime in the past. After all, if their key characteristics, such as income, have changed substantially since vehicle registration, drivers may have adjusted their vehicle choices to better suit their financial and operational needs. When estimating the ICLV model, I assumed that drivers' fuel type choices are conditional on their ridehailing intention, even though these decisions are often made simultaneously in practice, along with other vehicle parameters (e.g., size, purchase costs). The survey collected details about all ridehailing vehicles (including make, model, and year), therefore, future studies can leverage this information to gain deeper insights into drivers' vehicle choices.

Acknowledgements

This study was made possible through a research grant from the California Air Resources Board (CARB) [award number: 21STC013]. Additional funding was provided by the 3 Revolutions Future Mobility (3RFM) program of the University of California, Davis. Special thanks to James Giller, Mischa Young, Yongsung Lee, Patrick Loa, and Giovanni Circella for their invaluable contributions as coauthors of this study. I extend my sincere gratitude to Junia Compostella, Rainer Lempert, Rik Williams, Peter Day, Sarah Cormack-Patton, Melanie Zauscher, Annalisa Schilla, Joshua Cunningham, Stephanie Seki, Joshua Huneycutt, Katherine Dillon, Natalie Reavey for their support for this project. However, the authors are solely responsible for interpreting the results and any errors.

6 Conclusion

6.1 Key Findings

The primary goal of this dissertation was to provide insights into the impacts of emerging transportation technologies and major social disruptions, such as the COVID-19 pandemic, on consumers' vehicle choices and mobility patterns. Additionally, it aims to identify practical pathways that can help reduce car dependence, promote the adoption of cleaner vehicles, and support the transition toward more sustainable transportation.

Specifically, my dissertation comprises four interconnected studies that explore the determinants of private vehicle ownership (Chapter 3), preferences towards the adoption of AFVs in the privately owned vehicle market (Chapter 2) and for ridehailing fleets (Chapter 5), as well as the adoption of shared mobility options (Chapter 4). Collectively, these studies span various societal conditions in the pre-pandemic, pandemic, and post-pandemic periods, using four different datasets collected between 2018 and 2024. A central theme across all four studies is the emphasis on modeling heterogeneity — in characteristics, preferences, behaviors, and choices — among various population segments. In Chapters 2, 3 and 5, I employed various forms of integrated choice and latent variable (ICLV) models, incorporating individual latent attitudes into the modeling framework, to account for unobserved heterogeneity in different contexts. In Chapter 4, I used a Latent Class Cluster Analysis (LCCA) to identify distinctive, unobserved subgroups of travelers. These methods enhance behavioral realism of my models and support the development of more targeted and effective policy recommendations. The four empirical studies presented in this dissertation and their key findings are as follows.

I investigated California residents' current vehicle fuel type choices and their future interest in AFVs using data from the 2018 wave of the California Mobility Panel Survey. The findings highlight the impacts of latent attitudes, socio-demographic characteristics, and the "neighborhood effect" (i.e., exposure to AFVs) on AFV adoption. As of 2018, AFV users still exhibited characteristics (e.g., *tech-*

savvy, highly educated) that are largely associated with early adopters of new vehicle technologies, as identified in previous studies. While some factors consistently affect both current choices and future interest in AFVs, others reveal notable differences, suggesting that the determinants of vehicle fuel type choice—and perceived motivations and barriers to AFV adoption—may evolve over time. For instance, the *car-utilitarian* latent variable was not significant in explaining current adoption, but significant in predicting future interest, indicating that some consumers may believe AFVs will become functionally more feasible in the future. Although current AFV users are more likely to also express future interest in AFVs compared to non-AFV users, a substantial portion of non-AFV users are also interested in adopting AFVs in the future. Unlike most existing studies, which rely on hypothetical discrete choice experiments with convenience samples, this study analyzed a representative sample (to reflect California adult population distributions to the extent possible), with respondents expressing their future expectations based on their actual knowledge and experiences. This provides a more realistic estimate of what the natural ceiling for the AFV market (41.4%) could be among the California population under current market conditions and highlights untapped opportunities to increase adoption. The findings offer valuable insights to policymakers aiming to improve AFV market forecasting and to accelerate AFV adoption in California. The findings can also be useful to inform AFV-related policy in other states with relatively lower market penetration than California.

At the current pace, vehicle electrification alone may not be sufficient to mitigate the negative impacts of private vehicles, especially if ownership and usage continue to grow or remain stagnant over time. I used a two-wave panel dataset to jointly examine the changes in household vehicle counts among US residents during the COVID-19 pandemic (spring 2020 to fall 2023) and in the post-pandemic period (fall 2023 to fall 2026). To better understand the impact of the pandemic on vehicle ownership decisions, the study incorporated both variables – such as age cohort and race/ethnicity – which typically remain constant for individuals over time, as well as dynamic variables – such as life events, and changes in commuting frequency due to the adoption of remote work – that capture changes between timepoints.

Some variables consistently impacted changes in household vehicle count at both timepoints. For instance, individuals in less stable life stages (e.g., younger adults) or those with special travel needs (e.g., families with children) were more likely to increase their vehicle count during and after the pandemic. However, other variables exhibited various levels of significance and impacts at different timepoints. Individual attitudes had minor impact on changes in vehicle count during the pandemic, apart from vehicle replacements. However, *novelty-seeking* individuals were found to exhibit greater volatility in their vehicle decisions after the pandemic, showing a higher likelihood of increasing, decreasing, or replacing their vehicles compared to making no changes. Moreover, pandemic-specific factors, such as COVID-related health concerns, vehicle supply shortages, financial uncertainty, and unstable remote working policies, appeared to discourage changes in vehicle count during the pandemic, yet these influences were attenuated after the pandemic. For instance, individuals with strong COVID health concerns and those with higher commuting frequency (and those who increased their commuting frequency) during the pandemic were less likely to have shed their vehicles. While changes in employment status during the pandemic had limited immediate effects on vehicle ownership, employment changes in the post-pandemic period significantly impact vehicle decisions. Finally, I found that past vehicle ownership decisions strongly shaped future choices: in particular, individuals who shed vehicles during the pandemic are more likely to acquire more in the future, thus canceling out most of the potential (temporary) impacts of the pandemic on vehicle shedding. The findings highlight the complexities of vehicle ownership dynamics due to major societal disruptions. I propose targeted policies for various population groups, addressing their unique mobility needs while promoting alternatives to reduce reliance on private vehicle ownership and usage.

Shared mobility options, such as ridehailing services powered by AFVs, have the potential to reduce the dependence on private vehicles. Using week-long GPS-based travel diary data collected in 2018/2019 in the four largest metropolitan areas in California, I classified travelers into four distinctive groups based on their usage frequency for various modes. The results highlight the high level of car dependence among residents of these regions, with over 80% of the respondents can be classified as car-oriented travelers (53% *Drive-alone Users* and 28% *Carpoolers)*, and only the remaining 20% who are more multimodal (15% *Transit Users* and 4% *Cyclists*). Each traveler group exhibits unique socio-demographic characteristics, as well as ridehailing adoption and usage patterns. Transit users are more likely to also be frequent ridehailing users, especially for pooled services. In terms of mode substitution, car-oriented travelers are more likely to replace their car trips with ridehailing services, while multimodal travelers are more likely to substitute their trips involving less-polluting modes with ridehailing services. As a result, the net environmental impacts of ridehailing services remain ambiguous due to the complexity of ridehailing trip profiles (e.g., variations in travel time, pooled versus non-pooled, whether trips involved clean-fuel vehicles). Nevertheless, the findings can assist practitioners in identifying ridehailing trips that could be incentivized and promoted versus those that may need be discouraged by offering other viable alternatives (e.g., public transit), depending on their trip characteristics and geographic contexts.

To maximize the environmental benefits of AFVs within ridehailing fleets, I explored the motivations and barriers to electrification among Californian ridehailing drivers, using data collected through a web-based survey in 2024 administered among ridehailing drivers. The vast majority of drivers registered only one vehicle on the TNC platforms, with only 13.2% registering BEV(s). Fuel efficiency is the most frequently cited factor that impacts drivers' choice of ridehailing vehicles. Additionally, over one-third of the drivers obtained their registered vehicles specifically with the intention of using them for ridehailing work. My analysis revealed important distinctions in socio-demographic characteristics between drivers who obtain their vehicle with the intention of using it for ridehailing services vs. those without. Drivers who obtain their vehicle with ridehailing intention often belong to socioeconomically disadvantaged groups (e.g., older drivers, renters in multi-family dwellings, and those relying solely on ridehailing as their source of income). I further compared the factors impacting vehicle fuel type choices across these two groups of drivers. Certain factors (e.g., housing type, "neighborhood effect") that I identified to be associated with AFV adoption among the general population can be generalized to ridehailing drivers. There are also factors (e.g., whether the vehicle is owned or rented through TNC rental program) that play a significant role among ridehailing drivers. Drivers with favorable attitudes toward EVs, who view EV adoption as aligning with social expectations, and who perceive fewer barriers to using EVs for ridehailing work are more likely to adopt them. I also identified the significant positive impacts of access to chargers and familiarity with EV incentives on EV adoption. However, a considerable portion of drivers lack access to home chargers and public chargers. Moreover, a notable share of drivers was entirely unfamiliar with any federal/state/local EV incentives, with lower-income drivers demonstrating lower awareness and utilization of these programs. These findings underscore the urgent need to expand charging infrastructure, and enhance awareness of EV incentives, especially those related to charging facilities (e.g., Charging Station Federal Tax Credit, California EV Charging Station Financing Program). My model results show that home chargers have a stronger impact on drivers who obtain their vehicle without ridehailing intention (who typically drive occasionally or part-time), while public chargers are more essential for those who get their vehicle with the intention of using it for ridehailing activities (who often drive full-time). To maximize cost effectiveness, policymakers should focus on promoting Level 2 chargers in residential areas for drivers who also use their ridehailing vehicles for household purposes, while prioritizing DCFCs in targeted public areas to minimize downtime due to mid-shift charging for full-time drivers. Federal incentives are especially influential for drivers with ridehailing intentions, thus prioritizing targeted education program to this driver group could result in promising uptake in EV adoption in ridehailing sector. These findings provide insights for policy makers to identify and address key obstacles to electrification, particularly among drivers from disadvantaged communities.

6.2 Limitations and Future Work

It is important to acknowledge several limitations of this dissertation. First, although I purposefully included these four studies in this dissertation to help inform one another, each study has its own specific timeline and study area, which limits the ability to generalize trends identified in one study to the context of another. Second, while efforts were made to improve the representativeness of the samples relative to the targeted population by implementing more sophisticated sampling strategies and applying weights (in Chapter 2, 4, 5), these methods may not fully address discrepancies between samples and the targeted population. In addition, weights were not applied in the panel study (Chapter 3) because constructing them is challenging due to panel attrition, when participants drop out of the study over time, and the evolving characteristics of the population. As a result, the generalizability of some findings from this dissertation may be constrained. Third, while I carefully considered an extensive list of variables in the model framework of each study, some missing variables, or imperfect data due to survey design have limited the analyses. For example, in Chapter 2, direct information on individuals' access to EV chargers was unavailable, which is a critical factor when modeling fuel type choices. In Chapter 5, the survey did not ask ridehailing drivers to specify which vehicle they obtained using federal, state, or local incentives. As a result, I had to remove these drivers from the modeling to avoid potential ambiguity. These challenges I encountered serve as important lessons for future survey design improvements. Finally, due to the already complex model frameworks, each study only focuses on one aspect of decision-making. For instance, Chapter 2 and Chapter 5 model fuel type choice for the vehicle "used most" by respondents and Chapter 3 models only the direction of the changes in vehicle count, not their magnitude. In practice, decisions related to vehicle fleet composition and features (e.g., costs, fuel type, size, range) are interdependent and far more complex. In fact, the dataset used in Chapter 3 includes detailed information on all passenger vehicles available to the households (e.g., make, model, year), and the dataset used in Chapter 5 contains such information on all registered ridehailing vehicles. Leveraging this rich information and jointly modeling multiple aspects of decision-making could provide a more realistic and nuanced understanding of individuals' vehicle-related choices.

Transportation technologies are evolving rapidly, and the lingering effects of the COVID-19 pandemic continue to impact various aspects of our lives. There is a pressing need for further research to deepen our understanding of how these technologies and social changes are transforming the transport sector, which can inform policies to improve the transportation system. Several opportunities exist to expand upon the empirical work completed as part of this dissertation.

Chapter 2 and 5 highlight that many individuals, including members of the general population and ridehailing drivers, lack pre-existing knowledge about EVs. As a result, car dealerships or TNC rental centers often serve as the first point of contact where consumers encounter this technology. The information provided, the barriers perceived, and the test-drive experience at point of sale can significantly impact consumers' decisions to purchase, lease, or rent EVs (Zarazua de Rubens et al., 2018). A potential research direction involves designing and conducting focus group discussions and discrete choice experiment surveys to evaluate the value and priorities consumers place on various EV attributes (e.g., range, battery health, incentives) presented at point of sale. This information will help shape more effective business and promotion strategies.

For electrifying ridehailing fleets specifically, California is still in the early stages of implementing the CMS regulation. Chapter 5 of this dissertation only serves as a baseline study, providing an initial assessment of the current state of California TNC drivers based on survey data from the first wave of the data collection. However, this study only scratches the surface of the available data. Future research could delve deeper into drivers' awareness and utilization of incentives. For instance, ordered models could be used to identify factors influencing varying levels of awareness, with the goal of pinpointing groups of drivers that would benefit most from targeted educational efforts. Additionally, by analyzing drivers' self-reported expenditure and revenue data associated with using EVs for ridehailing work, future studies could estimate the total cost of ownership for both new and used EVs compared to conventional gas vehicles. This information could evaluate the financial viability of using EVs for ridehailing, helping drivers make more informed decisions about their vehicle choices. Following-up surveys are also necessary to monitor the impact of CMS on drivers over time. For example, researchers could investigate which drivers transition from gas vehicles to EVs between survey waves, their motivations, and conversely, which drivers revert from EVs to gas vehicles, along with the barriers they encounter. These findings could inform the development of complementary policies to support CMS implementation while minimizing negative impacts on TNC drivers, particularly those from socioeconomically disadvantaged groups.

Finally, Chapter 4 of my dissertation revealed that California residents were heavily car-dependent in the pre-pandemic era, a trend that appears to have intensified during and after the pandemic, as suggested by the findings in Chapter 3. The observed increase in car ownership and usage underscores the need for ongoing efforts to understand shifts in individual activity-travel patterns in the post-pandemic period. These efforts should focus on examining changes in travel mode preferences, variations in VMT generation by trip purposes, and the implications of these changes on transportation systems. Governments, employers, and transport agencies could use this knowledge to implement more effective hybrid working policies, to better allocating transportation investment budgets to support diverse modes of transportation that cater to various traveler groups.

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