

A Model of Electric Vehicle Adoption and Motivating Reasons for Adoption

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ABSTRACT

While there is broad interest in understanding electric vehicle (EV) adoption patterns, many existing studies are confined to an examination of stated adoption intentions rather than revealed behaviors. Accordingly, we use a survey of 1,098 California households to examine the ways that demographics, lifestyle preferences, and perceptions of EV characteristics impact revealed adoption behaviors. In addition, the survey asked current EV owners to rank the importance of a set of factors that influenced their adoption decision, enabling an investigation of the motivations for EV ownership. By modeling EV adoption and the motivations in a joint binary-ranked choice framework, we account for sample selection effects, enabling us to generalize these motivations to the population at large and identify policy measures to encourage adoption among those who have yet to adopt. This approach provides insights into the implementation of EV incentive policies, deployment of EVs, and development of EV charging infrastructure.

Keywords: Revealed Preference, Revealed EV Behavior, Rank-Ordered Model, Joint Mixed Model, EV Adoption Latent Perceptions

1. INTRODUCTION

The transportation sector is one of the largest contributors to greenhouse gas emissions and accounts for nearly 45% of global oil demand, primarily due to the widespread use of internal combustion engine vehicles (ICEVs) (IEA, 2023). In fact, while the United States has seen an overall reduction of greenhouse gas emissions of around 3% since 1990, emissions in the transportation sector have increased by over 20% in the same period (EPA, 2024). In addition to climate impacts, vehicle emissions have been shown to cause increased risks of respiratory and cardiovascular diseases, lung cancer, and childhood asthma (Brugge et al., 2007; Luo et al., 2022). Thus, there is growing recognition of the need to reduce transport-related emissions, and policymakers have increasingly looked to electric vehicles (EVs) as an important tool to do so.

While EVs have broad potential to combat climate change and provide significant benefits for individual owners, adoption rates have, thus far, remained relatively low (EIA, 2023). This situation has created a “chicken-and-egg” problem; while there is interest in better understanding why adoption rates have been low (and how EVs can be promoted) through a study of actual individual-level adoption behaviors, the low uptake of EVs has made such investigations of individual-level behaviors difficult. In particular, most existing EV adoption studies have been confined to an examination of *stated intentions* rather than *revealed behaviors* (see Pamidimukkala et al., 2024). Notably, while stated intentions are often viewed as good antecedents of future behaviors, there is also empirical evidence from a wide range of contexts that stated intentions do not always align well with revealed behaviors (Fifer et al., 2014; Z. Li et al., 2020). This has also been shown in an aggregate sense in the context of EV adoption (Jia and Chen, 2021). For instance, while younger adults generally have a stronger intention to adopt EVs compared with older adults, counties with larger shares of older, retired, individuals tend to have more registered EVs (see Jia and Chen, 2021).

A study of EV adoption revealed behaviors at the individual decision-making level would be valuable to add fresh insights regarding the future of the EV market. Fortunately, recent growth in EV adoption in parts of the United States has made such a study possible. Specifically, EV sales have grown steadily in California, making up 25% of all light-duty vehicle sales in 2023 (California Energy Commission, 2024). Accordingly, in this study, using data from California (collected between November 2022 and January 2023), a state which accounts for nearly 37% of registered electric vehicles in the United States (EIA, 2023), we examine the ways that demographics, lifestyle preferences, and perceptions of EV characteristics impact revealed EV adoption behaviors.¹ For the purposes of our study, we consider plug-in EVs, which includes battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). We focus on these technologies as they are emerging as the most prevalent and likely replacements for ICEVs in the transition to sustainable passenger transportation. In addition to the binary adoption decision, using information elicited from a survey that asked current EV owners to rank the importance of a set of factors that influenced their adoption decision, we are able to investigate the motivations for EV ownership and the ways these reasons translate into actual EV adoption behavior (also referred to as purchase behavior in this paper). Importantly, by modeling EV adoption and the motivations in a joint framework, we account for sample selection effects. This allows us to generalize the motivations for EV adoption to the population at large (including current non-EV owners), and in turn identify potential policy measures that may promote EVs in the overall marketplace and encourage EV adoption among those who have yet to adopt EVs. In particular, our model provides important insights for the deployment of EVs, the development of EV charging infrastructure, and the implementation of information and incentive policies to promote EV adoption.

The next section provides an overview of the existing literature on EV adoption. Section 3 presents the characteristics of the dataset along with the generalized heterogeneous data modeling (GHDM)

¹While our discussion references results and literature from a variety of contexts with different geographic, temporal social, and economic characteristics to provide a broad picture of EV adoption patterns, the dataset employed in this study was collected strictly from California homeowners, and caution needs to be exercised in any generalization from our study to other geographic, social, and economic contexts.

framework employed to jointly analyze the binary EV adoption decision and the ranked choice of the motivations from current EV owners. To our knowledge, this is the first application of the GHDM framework to a sample selection framework where the outcome equation takes the form of a rank-ordering (this corresponds to the motivations for EV adoption in our empirical context), while the selection equation takes the form of a binary choice (whether or not an individual currently is an EV adopter). Section 4 presents the model estimation results and interpretations as well as the model fit and the approach used to compute the effect-sizes of each exogenous variable on EV adoption. Section 5 discusses several implications of this research for EV incentives and policies, vehicle development and marketing, and planning and infrastructure development. Finally, Section 6 concludes the paper with a summary of important findings and identification of future research directions.

2. LITERATURE OVERVIEW

Much of the existing EV adoption related literature has focused on two areas: (1) studies of the intention to buy an EV using stated (not revealed) preference surveys, and (2) examinations of aggregate (not individual) trends in EV ownership levels across geographic areas. Each of these areas has relevance for the current study, as the first captures the characteristics and attitudes that impact adoption intentions and the second accounts for the revealed aggregate behaviors of EV owners. Additionally, while there are many ways that determinant variables have been grouped in existing EV adoption studies, we do so in a specific way by grouping into four categories that highlight the importance of individual attitudes and perceptions: (1) psychological factors, (2) contextual (or political/structural) factors, (3) technological (or situational) factors, and (4) demographic factors. This grouping is consistent with those used in several existing EV studies (see Li et al., 2017; Singh et al., 2020 for comprehensive reviews using similar groupings of determinant variables). The framework also aligns with the Theory of Planned Behavior (TPB; Ajzen, 1991) and the Technology Acceptance Model (TAM; Davis, 1989; Venkatesh and Davis, 2000). In particular, TPB identifies (a) attitudes toward a behavior, which are well aligned with the first set of “psychological factors” in our grouping, and (b) subjective norms or the general views of people, which are closely tied with our second set of “contextual factors.” Additionally, the TAM identifies perceived usefulness and perceived ease of use as important elements in technology adoption, both of which are closely tied to our third set of “technological” (or situational) factors. The last set of “demographic factors” are included because they influence attitudes, perceptions, and subjective norms, but also because they serve as proxies for perceived behavior control as identified by the TPB (that is, whether a new product/technology such as EVs is viewed as being within the technology skill set level for operation by an individual, which can itself depend on such demographic factors of the individual as age, gender, income, and formal education level). Of course, we will also readily admit that there is some overlap in the four categories of variables identified and close connections between the variables grouped into the four categories. But our grouping provides a useful structure to discuss the broad range of factors at play in EV adoption decisions.

2.1 Individual Adoption Intentions

2.1.1 Psychological Factors

Recent research has suggested that perceptions of EVs play a large role in determining EV adoption, typically even more than objective EV factors (see, for example, Zhang et al., 2022; Rye and Sintov, 2024; Pamidimukkala et al., 2024), potentially resulting in misconceptions about the value of EVs (Junquera et al., 2016; He et al., 2018). For instance, studies (Ayetor et al., 2023; Rye and Sintov, 2024) have indicated that, for individuals who are not too knowledgeable about EV technology, there is a perception that EVs entail higher maintenance costs than ICEVs. In contrast, for those with specific knowledge about EV maintenance costs, the more objective reality of the economic competitiveness of EVs over the long run appears to contribute to EV adoption. Similarly, greater knowledge of EVs and practical experience with EV charging have been shown to improve attitudes towards EV adoption, particularly by helping alleviate range anxiety, which generally impacts perceptions of BEVs more so than PHEVs, regardless of whether individuals live in areas with high or low public charging station availability (Ackaah et al., 2022; Ju and Hun Kim, 2022). Additionally, perceptions regarding non-ionizing radiation from electric vehicles have

been shown to influence consumer choices, reducing intentions for PHEV adoption (Tchetchik et al., 2024). For these reasons, it is important to consider how individuals perceive EVs, not solely their objective characteristics (Pradeep et al., 2021; Ayetor et al., 2023). Beyond perceptions of EVs themselves, psychological and attitudinal characteristics (such as individual-level attitudes towards climate change, comfort with technology, and views of vehicle ownership) directly influence EV adoption intentions. For instance, feelings about the importance of sustainability are a crucial predictor of adoption, particularly due to the widespread portrayal of EVs as a climate change solution (Adnan et al., 2018; Zhang et al., 2018; Asadi et al., 2021; Kautish et al., 2024). Similarly, driving hedonism has been shown to impact vehicle preferences, as driving experience differs in vehicles with different fuel types, with individuals with high levels of driving hedonism generally choosing ICEVs or PHEVs rather than BEVs (Tchetchik et al., 2020). Finally, social expectations and peer influences have significant impacts on EV adoption, particularly as attitudes toward the role of the vehicle (as primarily functional or as a status symbol) relate to these peer effects (Burs et al., 2020; Cui et al., 2021; Xia et al., 2022; Deka et al., 2023; Buhmann et al., 2024).

2.1.2 Contextual Factors

Contextual factors include the local infrastructure and policy incentives that are available. The availability of EV charging infrastructure is one of the most commonly cited barriers to EV adoption, particularly for BEVs compared with PHEVs (Hardman et al., 2018; Dutta and Hwang, 2021; Buhmann et al., 2024; Pandita et al., 2024). Although most individuals report that they intend to charge primarily at home or the workplace (see White et al., 2022; Hanni et al., 2024), the lack of charging infrastructure in public spaces limits the flexibility of BEV users and reduces adoption intentions (Dong et al., 2020; Pandita et al., 2024). Economic factors such as gas and electricity prices have also been shown to affect adoption intentions, as consumers in areas with low electricity prices and rising gas prices may favor EV adoption (Javid and Nejat, 2017; Rye and Sintov, 2024), though consumers may be less sensitive to changes in electricity prices than gas prices (Bushnell et al., 2022). Similarly, government subsidies and policy incentives, particularly financial incentives, have been shown to contribute to the perceived economic value of EVs and increase adoption intentions (Kim et al., 2018; Xia et al., 2022). Other policy incentives that have been shown to positively influence adoption intentions (though generally to a lesser extent in the United States) include special privileges for EV owners, such as parking privileges (Wolbertus et al., 2018; Lashari et al., 2021), driving privileges in carpool or bus-only lanes (Lu et al., 2020), and license plate lottery incentives (She et al., 2017). Finally, the environmental efficiency of EVs is different for BEVs and PHEVs, and depends significantly on the energy source mix used to produce electricity, so the local electricity system and government policies on greenhouse gas emissions in the electricity sector may impact adoption intentions (L. Li et al., 2020; Ben Ali and Boukettaya, 2023).

2.1.3 Technological Factors

Technological factors include the broad set of economic and technological considerations that influence EV performance compared with that of ICEVs. The high purchase cost of EVs (particularly BEVs) has been shown to be a significant barrier to adoption intentions, resulting in significantly lower adoption rates for low-income populations (Park et al., 2018; Mandys, 2021). Lower fuel and maintenance costs can make EVs economically competitive with ICEVs in the long term, but they are still only feasible for those who can afford the high initial cost to reap these longer-term rewards (Plötz et al., 2014; Pradeep et al., 2021). A wide range of technological factors also influence adoption, including road performance, driving range, safety, and environmental impact. Concerns about battery range have been shown to be a significant barrier, though less so for PHEVs which provide the flexibility of using the gas engine (Higueras-Castillo et al., 2021; Ju and Hun Kim, 2022; Wang et al., 2022). Charging speed and range are also particularly important for those intending more long-distance travel, who are particularly reliant on the availability of charging stations (Haustein et al., 2021; Jang and Choi, 2021; Krishnan and Koshy, 2021; White et al., 2022). Other vehicle features including initial acceleration rate, noise, driving smoothness, and ease of use can also influence adoption and differ significantly between different types of EVs (Tu and Yang, 2019; Zhang et al., 2022; Bhat et al., 2024).

2.1.4 Demographic Factors

Younger drivers show high levels of interest in EVs, perhaps due to their interest in environmental benefits as well as in new technologies in general (Sovacool et al., 2018; Huang and Ge, 2019; Chen et al., 2020). However, the first adopters of EVs tend to be middle aged, largely due to the high initial costs that are pose a barrier for younger adults (Habich-Sobiegalla et al., 2019; Lashari et al., 2021). Gender differences in EV interest related to different EV features are also evident; Men show more interest in the technological advancements in EV technologies (and particularly so for BEVs) and perceive greater advantages to EV ownership (Wang et al., 2021; Ali and Naushad, 2022), while women prioritize the environmental benefits associated with EVs but may be more wary of difficulties associated with charging, leading to a stronger preference for PHEVs among women (Ziefle et al., 2014; He et al., 2018). In California, evidence suggests that existing EV owners are predominantly male (Lee et al., 2019). In addition, individuals with more education tend to be more inclined towards both PHEVs and BEVs, due to increased environmental concern and greater awareness of the potential technological and economic benefits of EVs compared to ICEVs (Li et al., 2017; Kim et al., 2019; Habich-Sobiegalla et al., 2019). At a household level, income has also been shown to influence adoption intentions, as high-income households can more easily afford the higher purchase prices needed to achieve the long-term economic and non-economic benefits of EVs (Plötz et al., 2014; Ramos-Real et al., 2018; Krishnan and Koshy, 2021; Munshi et al., 2022; Osipenko, 2024). Finally, findings related to the impacts of home ownership and housing type on EV purchase intention have been mixed. However, studies have generally found that access to a consistent parking and charging location (whether in-home or provided by an apartment complex) is important for EV adoption, and particularly so for BEV adoption since there is no alternative to charging (Egnér and Trosvik, 2018; Lashari et al., 2021).

2.2 Aggregate EV Ownership Trends

Models of aggregate trends in EV ownership have largely focused on contextual and demographic factors. Several aggregate studies have reported that many of the contextual factors significantly impacting individual adoption intentions also manifest themselves in actual aggregate adoption patterns (for a more detailed review of studies in this area, see Austmann, 2021). For instance, aggregate models do point to a significant relationship between of EV charging infrastructure and EV adoption levels, finding much higher adoption rates (particularly for BEVs) in areas with developed public EV charging infrastructure (Mersky et al., 2016; Adhikari et al., 2020; Bhattacharyya and Thakre, 2020). Similarly, aggregate studies have assessed the impacts of financial incentives on EV adoption and found that acquisition subsidies, tax incentives, electricity subsidies, and added taxes for fossil fuels are all significantly related to higher EV adoption rates (Sierzchula et al., 2014; Hardman et al., 2017; Wee et al., 2018; Xue et al., 2021). In fact, these financial incentives, particularly those that impact initial purchase prices, seem to play an even larger role in actual adoption patterns than suggested by studies of stated intentions (Clinton and Steinberg, 2019; Jia and Chen, 2021; Künle and Minke, 2022). Similarly, other local conditions, such as gas prices (Chandra, 2022), non-economic incentives (Jenn et al., 2018), different modes of electricity generation (Mekky and Collins, 2024), and local climate conditions (Yang et al., 2023) have been associated with EV adoption rates.

As far as demographic trends, aggregate adoption studies have observed that EVs are adopted first in areas with higher median incomes and higher levels of educational attainment (Xue et al., 2021; He et al., 2022). Adoption is also more prevalent in suburban areas with high home ownership rates and relatively well-developed infrastructure (Mukherjee and Ryan, 2020; Gehrke and Reardon, 2022). Further, these aggregate studies have suggested that individuals living in multifamily homes or apartments are less likely to adopt BEVs than those living in single-family homes, likely due to challenges associated with home charging. Finally, several studies have shown that EVs tend to be adopted in dense clusters, even after accounting for policy and infrastructure changes, due perhaps to peer effects that result in significantly higher adoption rates once others begin to adopt EVs near an individual's home or workplace (Liu et al., 2017; Chakraborty et al., 2022).

2.3 Study in Context

Motivated by the need to better understand revealed EV adoption behaviors at an individual level, our study contributes to the literature in several important ways. First, we examine the factors that lead to EV adoption using individual-level revealed preference data, as opposed to earlier studies that have predominantly used stated intentions or aggregate spatial trends. Only a few existing studies have modeled adoption behavior using revealed data (see Nazari et al., 2019; Brückmann et al., 2021), and our study is the first to comprehensively also model the reasons for EV adoption using data from actual adopters. Second, we model the importance of a set of reasons for the adoption of EVs using a rank-based approach. While several studies have examined the characteristics of existing EV owners and their reasons for adopting EVs using descriptive methods, none have modeled these behaviors systematically (see, for example, Vassileva and Campillo, 2017; Anfinssen et al., 2019). We consider a comprehensive set of factors that motivate EV adoption, including economic factors (such as concerns about rising gas prices and the availability of incentives), EV interest and experience (such as overall interest in EV technology, interest in a specific brand or model, and experience through test drives), social influence through friends or family, the ability to charge at home, and concerns about climate change. Further, the use of a ranked preference design rather than a first-choice preference design allows more information to be determined from each individual's selection and is more behaviorally appropriate for a context where the decision may not be driven by a single motivation (Nair et al., 2018, 2019), as is the case with EV adoption. Third, we include a comprehensive set of exogenous variables to accommodate heterogeneity in EV preferences based on individual demographics (such as age, race, gender, and educational attainment), household characteristics (including household composition, income, and home ownership status), and characteristics of the home location (including population density, intersection density, and charging density). This allows us to determine how overall adoption patterns vary across demographic groups, as well as capture differences in the motivations across individuals, thus enabling the design of customized EV adoption policies directed toward specific population groups. Fourth, we consider how attitudes and EV perceptions impact adoption using four latent constructs. Two of these correspond to psychological/lifestyle-related latent constructs: (a) green lifestyle propensity (GLP) and (b) vehicle functionality preference (VFP) (VFP refers to the intensity with which vehicles are viewed as serving a functional role rather than serving as a social status symbol). Both of these factors have been shown in existing studies to influence adoption behaviors (Adnan et al., 2018; Deka et al., 2023; Buhmann et al., 2024). The other two latent constructs are more closely associated with the contextual and technological factors discussed earlier: (a) EV (relative to ICEV) cost and maintenance perception (CMP), and (b) EV battery range and charging perception (BRP). Given that several studies have found widespread misconceptions about EV features (see He et al., 2018; Kautish et al., 2024), considering individual perceptions associated with contextual/technological factors directly is more likely to reflect how individuals are actually making adoption decisions. Fifth, we model the adoption dimension and ranked importance of factors contributing to adoption together in a joint model that accommodates unobserved correlation effects between adoption and the ranked importance of factors. This allows for the possibility of “self-selection” effects among EV owners (that is, existing EV owners may be more likely to prioritize some reasons for choosing EVs than those who have yet to adopt), enabling us to identify the importance of EV adoption motivation factors for any individual in the general population, regardless of whether an individual currently owns an EV or not. For instance, an individual who has an intrinsically elevated preference for sustainability (say an unobserved factor) will be more likely to adopt EVs overall, and to do so specifically because they have concerns about climate change. If the EV adoption and EV adoption motivation reasons are modeled independently ignoring the correlation due to the “sustainability preference” unobserved factor, concerns about climate change (as a motivating reason for EV adoption) would be overestimated for any random individual in the population (who would not be as sustainability-concerned as an EV adopter). At an aggregate population level (of current EV owners and current EV non-owners), the result would then be an overestimation of the true benefits of highlighting environmental benefits as a way to promote EV adoption, potentially leading to misinformed policy investments. By estimating the EV adoption and EV motivating factors jointly (that is, accounting for the sample selection in EV motivating factors based on EV adoption, as caused by common unobserved

effects), however, we are able to more accurately identify the EV motivating factors for any member of the general population, allowing informed policy investments to promote EV adoption. Sixth, as another methodological advance, we consider the latent constructs themselves to be endogenous to the adoption/motivation outcomes by allowing correlation effects between the stochastic terms embedded in the latent constructs and the error terms in the adoption/motivation equations. This is important because many unobserved attitudes and lifecycle factors (not considered by themselves as latent constructs because of a lack of indicators in the survey) that influence the latent constructs may also influence the EV adoption/motivation outcomes. For instance, individuals who generically are curious about technology (say an unobserved individual variable, as in the current study) may be higher on the BRP latent construct scale (because they would be more likely to seek out information about EV battery technology) and, at the same time, be intrinsically more likely to buy an EV. If such a correlation does exist, but is ignored, it would lead to an overestimate of the effect of the BRP latent construct on EV adoption. Similarly, these same generically technology-curious individuals who load higher on the BRP latent construct may also be more likely to rank “high gas prices” as a top motivator for EV adoption. If this correlation exists, but is ignored, it would again lead to an overestimate of any positive effect of the BRP latent construct on choosing “high gas prices” as an EV adoption motivator. Finally, we translate model estimates into average treatment effects of exogenous individual/household-level variables on EV adoption, further disaggregating these effects based on indirect effects (through the latent constructs) and a direct effect, providing deep insights into ways that EV adoption may be promoted in the general population.

3. METHODOLOGY

3.1 Data Description

The data for this study are drawn from a survey of California households conducted between November 2022 and January 2023. Households were selected into the sample in two ways (for a detailed discussion of the survey collection, please see Firestone, 2022). First, households with EV charging permits and solar panel permits were identified using the BuildZoom data platform (BuildZoom, 2022). From this sampling frame, 2,000 randomly selected households with solar-only permits, 2,000 randomly selected households with EV-only charging permits, and all 1,073 households that had both a solar and EV charging permit were invited to participate in the study. Invitations were mailed to each household, addressed to the listed homeowner, inviting them to take the survey online. Of these, a representative from each of 561 households responded to the survey online. Second, a general population survey of California homeowners was conducted by YouGov (YouGov, 2022). 2,948 individuals from the YouGov active California panel were invited to participate, of whom 810 complete responses (from a single individual to represent each household) to the online survey were received. Subsequently, YouGov performed census matching to reach a final sample of 750 homeowners. Across the two data collection efforts, a total sample size of 1,311 households resulted. Of these, 213 additional respondents with incomplete data were removed, leaving a final sample size of 1,098 for the analysis (important to note is that the labels “household” and “respondent” or “individual” are synonymous, given a single individual from each household provided information related to the entire household). Of course, one limitation of this approach is that attitudes/opinions are only collected from a single adult to represent those of the entire household, while, in reality, these vehicle ownership decisions are likely made at the household level based on the need, attitudes, and opinions of all household members. Still, the use of this individual-level data to represent the attitudes/opinions of the entire household is supported by evidence from sociological and psychological literature (Davis and Rusbult, 2001; Levy et al., 2008; Li et al., 2025) suggesting that, because household-level decisions are made through negotiation and collaboration among household members, any individual who reports motivating factors would provide information representing those of the household as a whole.

The survey was undertaken as part of a larger research project on the co-adoption of EVs and rooftop solar panels. The survey instrument was designed based on the literature, intuition, and semi-structured interview with EV-only adopter, solar-only adopter, and EV-solar co-adopters undertaken in the first phase of the research project (Bull et al., 2025). As part of the survey, respondents were asked about their current ownership of EVs as well as attitudes and opinions relating to vehicle ownership and vehicle

characteristics, barriers to adoption of EVs, and environmentally friendly practices and technologies in general. The survey also collected individual- and household-level demographics as well as dwelling unit and residential location characteristics. Finally, of particular importance for the current study, the survey asked current EV owners (that is, the individual respondents from households that own EVs) to rank the importance of a set of motivating factors that led them to consider buying an EV. The set of motivations included were based on the results of the semi-structured interviews in the previous phase of the data collection as well as aligning with five classes of values from the Theory of Consumption Values (Sheth et al., 1991): Functional, Emotional, Social, Epistemic, and Conditional (see Bull et al., 2025 for a detailed discussion of the semi-structured interview results and theoretical background that led to the development of this set of motivating factors). Specifically, participants were asked to rank the top three choices from the following list of factors: (1) Rising gasoline prices, (2) To take advantage of available incentives, (3) Interest in the technology, (4) Interest in specific brand/model of electric vehicle, (5) Test drove one, (6) Heard about EVs from friends/family or colleagues, (7) The ability to charge/"refuel" at home, (8) Concerns about climate change, (9) To increase household electricity consumption as we were planning to get solar panels, (10) Media/advertising, (11) Passenger in one, (12) Saw one at work or others with one, and (13) Something else (please specify). Because of the handful of respondents who selected the final five factors, we removed these and modeled only the responses for the first eight factors, retaining only those current EV owners who had at least one of the eight alternatives selected.² The net result is that, while every EV owner had a top ranked alternative, only a subset had a second ranked response, and a further subset had a complete set of three ranked responses.

An important point needs mention here. Due to the retrospective nature of this motivational question (asking respondents to recall the motivations at play during the adoption decision), we must acknowledge the potential that these responses may be influenced by recall bias. However, there are several reasons to believe that such recall biases will be relatively small in the current empirical context. First, the questions ask about general summative motivations and feelings surrounding EV adoption rather than finer aspects of behaviors/actions such as specific dates of EV purchase or precise tradeoff calculations that may have been made before purchasing an EV. The general survey literature (see Abadie et al., 2021; Helm and Reyna, 2023) has established that summative feelings are more easily recalled and ranked than finer aspects of decision making, the latter being more prone to inaccurate recall, scale effects, and telescoping. Second, the broad motivational factors align with how individuals store and retrieve memories, and the use of choice categories for response helps to facilitate memory retrieval (Müggenburg, 2021). Third, the decision to adopt EVs is not a daily or routine decision, but more of a one-off major purchase decision that is made with careful and considerable deliberation. In such non-routine and relatively one-off kinds of contexts, respondents are more easily able to recall and contextualize motivations even after a long stretch of time since making the choice (Dilevski et al., 2021; Kraemer et al., 2022).

In addition to the survey responses, additional geographic data were appended to the dataset based on each respondent's zip code. First, population statistics were included using the EPA Smart Location Database (Chapman et al., 2021). Second, EV charging station prevalence by zip code was determined using the U.S. Department of Energy Alternative Fuels Data Center (National Renewable Energy Laboratory, 2024).

3.1.1 Exogenous Variables

Descriptive statistics of the sample are shown in Table 1, along with a comparison to 2022 American Community Survey 5-year estimates for the state of California (U.S. Census Bureau, 2023). The sample underrepresents younger individuals (especially in the age group of 18-34 years), non-white individuals, women, employed individuals, and those with lower levels of educational attainment. For household-level

²Note that the order of the factors included here is not the same as the order shown in the survey. Additionally, each of the final five factors (which were removed from the analysis) were ranked in the top three motivating factors by less than 6.5% of current EV owners. Only five households were removed because they did not select at least one of the top eight alternatives.

demographics, there is an overrepresentation of households with two or more adults, high-income households, households without children, and those living in single-family (detached) homes. We categorize household type as either single-family (detached) homes or multifamily homes (including apartments and attached dwellings; this segment is made up primarily of duplexes in the current sample). The over-representation of households living in single family homes is unsurprising given that the sampling frame was based, in part, on solar panel ownership and building permits and consisted solely of homeowners. Finally, two metrics are used to characterize the residential location of each respondent. First, respondents are considered to be in either high population density areas (more than 9,597 people per mile) or low population density areas (equal or fewer than 9,597 people per mile), based on the population weighted average density of all zip codes in the state. Second, the density of electric vehicle charging stations is determined by the number of publicly available stations (at any charging level) per square mile in each zip code as of January 2023 and is categorized into three levels of low (10 or fewer stations per square mile), medium (between 10 and 50 stations per square mile), and high (more than 50 stations per square mile). Individuals living in areas with high charging station density are overrepresented compared with population weighted estimates from the U.S. Department of Energy Alternative Fuels Data Center, which is again unsurprising given that respondents were selected in part on EV ownership.

The observed skews in the exogenous variables are to be expected in this sample due to the choice-based sampling mechanism used in data collection. This choice-based sampling approach implies that an unweighted estimation approach would lead to biased parameter results (see Wooldridge, 1995; Solon et al., 2015). Therefore, to accommodate the choice-based sampling, a series of sampling weights were generated using iterative proportional fitting based on overall EV ownership and solar panel ownership levels in California (see California Energy Commission, 2024) to avoid estimator inconsistency. This weighted exogenous sample maximum likelihood (WESML) estimator is consistent under very general conditions for a choice-based sample, though it also requires the computation of a robust sandwich covariance matrix to obtain parameter standard errors (Manski and Lerman, 1977).

3.1.2 Endogenous Outcomes

The main outcomes in this study include a binary outcome for EV adoption and a rank-ordered outcome representing the motivating factors that prompted existing EV owners to consider buying an EV. Of the 1,098 individuals/households included in the sample, 417 (38.3%) individuals/households owned an EV using the unweighted shares (this includes all individuals who owned either a BEV or PHEV at the time of the survey). After applying the sampling weights, the EV share in the sample corresponds with a weighted share of 5.17%, aligning with overall EV ownership levels in California in early 2023. In our analysis, because of the small number and weighted share of EV-owning households, we make a distinction in preference between BEV and PHEV ownership solely based on individual/household demographics and latent constructs, maintaining the same kernel error term for both BEVs and PHEVs. We achieve this by defining a PHEV-ownership indicator and interacting this indicator with the remaining exogenous variables as well as the latent constructs. Effectively, the assumption here is then that, while the overall error term distributions in the BEV and PHEV utilities do differ because of the interactions of the PHEV indicator with the stochastic latent constructs, conditional on the latent constructs, the determinant factors not considered in our analysis are identical in the BEV and PHEV utilities. In this model structure, the main exogenous/latent construct effects in the adoption equation represent the effects for BEV adoption, while the interaction effects represent the difference in the preferences for PHEV adoption relative to BEV adoption. Where no interactions are present, the coefficients indicate an effect for EV adoption in general (with no statistically significant difference between BEV and PHEV adoption).³

³For completeness and preciseness, we should note that the sample included 285 households owning only a BEV, 79 households owning only a PHEV, and 53 households owning both a BEV and PHEV (for the total of 417 EV owners). Our PHEV indicator took the value of 1 for the total of 132 (79+53) households that owned a PHEV. Thus, to be fastidious, the interaction effects represent the difference between households that own a PHEV relative to households

The distribution of responses to the rank-ordered outcome is presented in Table 2 for both the unweighted and weighted shares. This question was only asked of current EV owners. Additionally, as discussed before, since only the eight most selected reasons were retained, not all EV owners have a full set of three rankings. Of the 417 EV owners, 285 had a full set of three ranked responses, 108 had only two ranked responses, and 24 had only a single ranked response (the percentages shown in Table 2 for the second and third columns in each panel are based on the number of participants with at least two or three ranked reasons, respectively, so all the columns sum to 100%). The sampling weights do not seem to significantly influence the distribution of motivating reasons that influence adoption, an unsurprising result given that they are only available for current EV owners. As may be observed from the table, concern about climate change is the most significant factor leading to EV adoption, with 34.5% of the sample selecting this factor as the most important. Interest in EV technology and rising gasoline process also appear to be important at this aggregate level. In contrast, having a test drive or hearing about EVs from friends or family members do not seem to be particularly important (with less than 5% of respondents ranking each of these reasons first). “Taking advantage of available incentives” and “The ability to charge/’refuel’ at home,” while not appearing as the top rank frequently, do appear frequently as the second or third rank in motivation. Overall, EV adoption, based at least on this aggregate descriptive analysis, appears to be driven more by climate change concerns and benefits of the technologies overall rather than peer effects or test drive experiences.

3.1.3 Latent Constructs

As discussed earlier in Section 2.3, we consider four stochastic latent constructs that are likely to impact EV adoption, two associated with psychological/lifestyle-related factors (green lifestyle propensity or GLP and vehicle functionality preference or VFP), and two associated with contextual and technological factors (EV cost and maintenance perception or CMP and EV battery range and charging perception or BRP). These constructs are latent and stochastic because they are not directly observed, but indicators for these underlying lifestyle and technology preferences/perceptions are available. The four constructs are also consistent with the TPB framework and the TAM model, discussed in Section 2, that emphasize the importance of attitudinal/lifestyle factors, subjective norms, as well as perceived usefulness factors in the context of technology uptake. Regarding the psychological constructs, extensive studies in transportation, information science, technology adoption, and the more general psychology/ethnography fields have validated the use of psycho-social identities of individuals in explaining the adoption of emerging technology (Astroza et al., 2017; Foroudi et al., 2018; Gunden et al., 2020; Marikyan et al., 2019). The two selected for inclusion in the current study (GLP and VFP) have been shown in existing research to be closely aligned with motivations for EV adoption, and GLP has emerged in existing work as particularly pivotal, as EVs have been positioned as important contributors to climate change mitigation (see Biresselioglu et al., 2018; Buhmann et al., 2024). Regarding the two latent constructs associated with contextual and technological perceptions of EVs, as discussed in Section 2.1, perceptions of EV characteristics are critical to adoption patterns, possibly even more so than their objective characteristics (Shrestha et al., 2022; Zhang et al., 2022). Further, results regarding these two perception-related constructs have clear implications for practical EV adoption policies, as determining how these perceptions (to battery technologies and charging stations as well as EV costs) are formed and how they contribute to adoption have direct implications for technology and infrastructure development, information campaigns, and incentive policies.⁴ Each of the latent constructs is discussed briefly below.

that own only a BEV. But, given the small number of households that own both a BEV and PHEV, we will glaze over this nuance in our results discussion and interpret the interaction effects as the preference difference between BEV and PHEV ownership.

⁴The dataset did include a larger set of indicators related with additional lifestyle preferences and perceptions of EVs. Based on these indicators, other latent constructs, including those associated with symbolic values, moral norms, emotional factors, and additional perceived usefulness factors were also constructed and considered. But an analysis of “between construct” and “within construct” variances (based on the battery of indicators), along with a

Many previous studies (Asadi et al., 2021; Kautish et al., 2024) have observed that environmental consciousness is closely associated with intentions to adopt electric vehicles, so it is expected that GLP will significantly and positively impact EV adoption and be most closely aligned with “concern about climate change” as the motivating reason for EV adoption. The second latent construct of VFP helps locate individuals on a continuum between individuals who view vehicles as a status symbol or signaling device versus individuals who view vehicles as primarily intended for functional purposes and mobility (see Burs et al., 2020; Buhmann et al., 2024). The VFP is constructed such that higher values of VFP refer to a higher preference of functionality over status signaling. Given that EVs remain high-cost investments and have often been marketed as a luxury product, it is likely that they appeal to some individuals as a status symbol (Sovacool and Axsen, 2018). At the same time EVs represent a functional advance in vehicle technology which may be attractive to some others. In our analysis, we are able to estimate the effect of VFP on adoption and motivating reasons and also capture variations in this effect across individuals by interacting VFP with demographic variables. The third CMP latent construct refers to the perception of the value of an EV (relative to an ICEV) over its lifespan, with higher values of CMP corresponding to more favorable views of an EV over an ICEV. We would expect that individuals with a high CMP would be more likely to adopt EVs and cite economic considerations (such as “rising gas prices” and “take advantage of incentives”) as important motivating factors in the adoption decision. Finally, the last BRP latent construct refers to the relative ease of using an EV for long distance trips and charging an EV (out of home) compared with fueling an ICEV, with the natural expectation that BRP would positively affect EV adoption and the consideration of such motivating factors as “interest in a specific brand/model” (given that individuals with a high BRP would not be so concerned about charging/functionality issues and can place greater emphasis on the type of EV vehicle they would like).

Figure 1 presents the list of indicators for each latent construct and the distribution of responses to each of the indicators based on weighted shares. Individuals appear to lie relatively uniformly on the greenness scale (the GLP scale), even if skewed slightly more toward being green overall. They appear to be more focused on functionality than status signaling (high VFP) in vehicle adoption/use, though the distribution of individuals on the specific indicator question of “A vehicle provides status and prestige” is more balanced. The distribution of the indicators for CMP shows that there may be more uncertainty, in general, about the relative difference in cost and maintenance between EVs and ICEVs, with a large number of respondents selecting “about the same” for the CMP indicators. Finally, respondents seem to be more skeptical of EV range, with most respondents indicating that EVs are “somewhat worse” or “much worse” than ICEVs for the BRP indicators.

3.2 Analytic Framework

The generalized heterogeneous data model (GHDM) framework developed by Bhat (2015) is used for this analysis. Figure 2 presents a visual representation of this framework. The annotations by the arrows between the many boxes correspond to the equation notations used in the next section on model formulation. Bhat’s GHDM model is adapted here to include a single endogenous binary choice outcome for EV adoption and one endogenous rank-ordered outcome for the factors motivating EV adoption (shown toward the right side of Figure 2). As mentioned in Section 3.1.2, we distinguish between BEV and PHEV ownership based only on individual/household demographics and latent constructs, while maintaining the same kernel error term for adoption of each type of EV. Thus, in the model structure, a single combined utility equation can be used to represent the binary EV adoption decision, where the utility differences between BEVs and PHEVs are identified through interactions between the PHEV indicator and the exogenous variables/latent constructs, while maintaining a single kernel error term.

A set of individual- and household-level variables (left side of the figure) influence each of these outcomes in two different ways: (1) directly through the arrows at the top and bottom of the figure going to

comprehensive testing of this larger set of developed constructs using a combination of exploratory and confirmatory factor analyses, resulted in only the four latent constructs used here turning up being statistically relevant. This was because of overlapping sets of indicators across the many theoretically-developed latent constructs.

each outcome (labeled “MEM” for the measurement equation model component of the GHDM), and (2) indirectly through the effects of these exogenous variables on a set of stochastic latent constructs (GLP, VFP, CMP, and BRP), positioned in the center of Figure 2 (this arrow from the exogenous variables to the latent constructs is labeled “SEM” for the structural equation model component of the GHDM). The four stochastic latent constructs are loaded on a set of observed indicator variables (positioned at the center-bottom of the figure) as well as effecting the set of endogenous outcomes to estimate (impute) the SEM component of the GHDM. These loadings and effects are identified by arrows originating from the box containing the latent constructs in the figure (these arrows are labeled “MEM” as these relationships are estimated as part of the measurement equation model component of the GHDM). In addition to capturing attitudes and perceptions that influence EV choices, the inclusion of the stochastic latent constructs facilitates a parsimonious correlation structure among the main outcome variables (see the two-headed arrow at the top of the box containing the stochastic latent constructs identifying the correlations among the latent constructs). Essentially, if a stochastic latent construct impacts both the EV adoption and an EV adoption motivating reason, the result immediately is a correlation between EV adoption and the EV adoption motivating reason (because of the stochasticity of the latent construct; that is, the unobserved error term embedded in the latent construct). This accounts for the self-selection bias caused by the fact that motivations for EV adoption are only observed for current adopters, as discussed earlier in Section 2.3. For example, if the GLP stochastic latent construct (which includes an unobserved component, say sustainability preference) positively affects EV adoption as well as the motivating reason of “concern about climate change,” as we observed in our empirical results discussed later, the net result is a positive correlation between these two dimensions that accommodates for self-selection effects.

Finally, the latent constructs are also allowed to be co-endogenous with the main EV outcomes (see the two-headed arrows connecting the stochastic latent constructs with each of the main outcomes in Figure 2), allowing for correlations between the latent lifestyle preferences and perceptions and the main outcomes of interest, again as discussed earlier in Section 2.3.

3.3 Model Formulation

As mentioned above, the main outcomes in this study consist of one binary outcome and one nominal rank-ordered outcome. Although the rank-ordered outcome is only available for current EV owners, the mathematical formulation of the GHDM model presented below is shown for an individual with an EV (who has an available set of rank-ordered reasons for adoption). For individuals who do not own EVs, the procedure needs only a slight modification to marginalize over the rank-ordered outcome such that only the EV ownership outcome (and the latent constructs along with their indicators) is relevant. In the presentation below, we suppress the index for individuals for ease in presentation. Also, note that each individual does have the possibility of owning an EV (in either of the BEV or PHEV variant forms), since both BEVs and PHEVs are available in the marketplace. Similarly, because of the fact that, for current EV owners, all the adoption motivating reasons were presented to respondents in the survey, all of these reasons are de facto available to be chosen within the top three reasons.

To begin, let l be the index for the stochastic latent constructs ($l = 1, 2, \dots, L$). In this case $L = 4$, corresponding to the two attitudinal constructs and two EV perceptions. Then, denote the underlying latent construct z_l^* , and write it as a function of covariates in the SEM model component:

$$z_l^* = \alpha_l' \mathbf{w} + \eta_l \quad (1)$$

where $\mathbf{w}$ is a $(D \times 1)$ vector of observed variables (excluding a constant), α_l is a corresponding $(D \times 1)$ vector of coefficients, and η_l is a random error term. The error vector η_l is assumed to be standard normally distributed and captures the effects of unobserved factors that influence the stochastic latent constructs, after controlling for observed demographics. We also define the $(L \times D)$ matrix $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_L)'$, and

the $(L \times 1)$ vectors $\mathbf{z}^* = (z_1^*, z_2^*, \dots, z_L^*)'$ and $\boldsymbol{\eta} = (\eta_1, \eta_2, \dots, \eta_L)'$. Thus, we may write Equation (1) in matrix form as:

$$\mathbf{z}^* = \boldsymbol{\alpha}\mathbf{w} + \boldsymbol{\eta} \quad (2)$$

In order to accommodate interactions among the unobserved latent variables, we allow a multivariate normal (MVN) correlation structure for $\boldsymbol{\eta}$. $\boldsymbol{\eta} \sim MVN_L[\mathbf{0}_L, \boldsymbol{\Gamma}]$, where $\mathbf{0}_L$ is an $(L \times 1)$ column vector of zeros, and $\boldsymbol{\Gamma}$ is an $(L \times L)$ correlation matrix (see the two-headed arrow at the top of the box containing the stochastic latent constructs in Figure 2).

Now, consider N ordinal outcomes (including the indicator variables for each of the latent constructs as well as ordinal main outcomes) and denote the index for the ordinal outcomes as n ($n = 1, 2, \dots, N$). In our current context, we include the binary variable for EV adoption in the model as an ordinal main outcome (because a binary outcome can be considered as a special case of an ordinal outcome with two categories). This is done simply so that the formulation of the GHDM includes only ordinal variables and the ranked outcome (rather than needing an additional separate binary outcome). It has no other implications for model specification or results. Therefore, $N = 13$, corresponding to a total of 12 indicators of the four latent constructs (three indicators for each latent construct) and the single ordinal main outcome. Also, let J_n be the number of categories for the n^{th} ordinal outcome ($J_n \geq 2$) and let j_n be the corresponding index ($j_n = 1, 2, \dots, J_n$). Also, for each ordinal outcome, let $\tilde{y}_n^*$ be the underlying latent variable whose horizontal partitioning leads to the observed outcome. Next, assume that the individual chooses the α_n^{th} ordinal category. Then, we can apply the usual ordered response formulation, for the individual, to write:

$$\tilde{y}_n^* = \tilde{\gamma}_n' \mathbf{x} + \tilde{\mathbf{d}}_n' \mathbf{z}^* + \tilde{\varepsilon}_n \quad (3)$$

with $\tilde{\psi}_{n,a_n-1} < \tilde{y}_n^* < \tilde{\psi}_{n,a_n}$, and where $\mathbf{x}$ is an $(A \times 1)$ vector of exogenous variables (including a constant) as well as possibly the observed values of other endogenous variables (included in a recursive fashion), $\tilde{\gamma}_n$ is a vector of corresponding coefficients to be estimated, $\tilde{\mathbf{d}}_n$ is an $(L \times 1)$ vector of loadings of each latent construct on the ordinal outcome, the $\tilde{\psi}$ terms represent thresholds to be estimated, and $\tilde{\varepsilon}_n$ represents the standard normal random error for the ordinal outcome. For the indicators, however, the $\mathbf{x}$ vector will not appear on the right side of Equation (3). Additionally, identification conditions are needed regarding the number of non-zero elements of $\tilde{\mathbf{d}}_n$ that are possible in each indicator equation (and across all indicator equations; see Bhat (2015) for additional details). For each ordinal outcome, the thresholds must be ordered $\tilde{\psi}_{n,0} < \tilde{\psi}_{n,1} < \tilde{\psi}_{n,2} \dots < \tilde{\psi}_{n,J_n-1} < \tilde{\psi}_{n,J_n}$, with $\tilde{\psi}_{n,0} = -\infty$, $\tilde{\psi}_{n,1} = 0$, and $\tilde{\psi}_{n,J_n} = +\infty$. Let $\tilde{\boldsymbol{\psi}}_n = (\tilde{\psi}_{n,2}, \tilde{\psi}_{n,3}, \dots, \tilde{\psi}_{n,J_n-1})'$ and $\tilde{\boldsymbol{\psi}} = (\tilde{\boldsymbol{\psi}}_1', \tilde{\boldsymbol{\psi}}_2', \dots, \tilde{\boldsymbol{\psi}}_N)'$. Stack the N underlying continuous variables $\tilde{y}_n^*$ into an $(N \times 1)$ vector $\tilde{\mathbf{y}}^*$, and the N error terms $\tilde{\varepsilon}_n$ into an $(N \times 1)$ vector $\tilde{\boldsymbol{\varepsilon}}$. Define the $(N \times A)$ matrix $\tilde{\boldsymbol{\gamma}} = (\tilde{\gamma}_1, \tilde{\gamma}_2, \dots, \tilde{\gamma}_N)'$ and the $(N \times L)$ matrix $\tilde{\mathbf{d}} = (\tilde{\mathbf{d}}_1, \tilde{\mathbf{d}}_2, \dots, \tilde{\mathbf{d}}_N)$, and let $\mathbf{IDEN}_N$ be an identity matrix of dimension N that represents the correlation matrix of $\tilde{\boldsymbol{\varepsilon}}$. Finally, stack the N lower thresholds for the decision-maker $\tilde{\psi}_{n,a_n-1}$ into an $(N \times 1)$ vector $\tilde{\boldsymbol{\psi}}_{low}$ and the N upper thresholds $\tilde{\psi}_{n,a_n}$ into another vector $\tilde{\boldsymbol{\psi}}_{up}$. Then, in matrix form, the measurement equation for the ordinal outcomes for the individual may be written as:

$$\tilde{\mathbf{y}}^* = \tilde{\boldsymbol{\gamma}}\mathbf{x} + \tilde{\mathbf{d}}\mathbf{z}^* + \tilde{\boldsymbol{\varepsilon}}, \quad \tilde{\boldsymbol{\psi}}_{low} < \tilde{\mathbf{y}}^* < \tilde{\boldsymbol{\psi}}_{up} \quad (4)$$

Next, consider a single nominal rank-ordered outcome variable for an individual. Let I be the number of alternatives available for ranking and let i be the corresponding index ($i = 1, 2, 3, \dots, I$). In our context, $I = 8$ for the eight factors included in the model. However, we present the framework for any number of ranked alternatives because the presentation simplicity is not affected by using a general formulation. Consider the ranked variable and assume the usual underlying random utility structure for each alternative i .

$$U_i = \mathbf{b}_i' \mathbf{x} + \mathcal{G}_i'(\boldsymbol{\beta}_i \mathbf{z}^*) + \varsigma_i \quad (5)$$

where $\mathbf{x}$ is an $(A \times 1)$ vector of exogenous variables as earlier, $\mathbf{b}_i$ is an $(A \times 1)$ column vector of corresponding coefficients, and ς_i is a random normal error term. Further, $\boldsymbol{\beta}_i$ is an $(N_i \times L)$ matrix of exogenous variables that interact with the latent constructs to influence the utility of each alternative, and $\mathcal{G}_i$ is a $(N_i \times 1)$ column vector of corresponding coefficients which capturing the effects of the latent constructs and their interaction effects. If each latent construct impacts the utility of each alternative purely through a constant shift in the utility function (with no interaction effects), $\boldsymbol{\beta}_i$ will be an identity matrix of size L , and each element of $\mathcal{G}_i$ will capture the effect of one of the latent constructs on the constant specific to alternative i of the ranked variable. Define the $(I \times 1)$ vector $\boldsymbol{\varsigma} = (\varsigma_1, \varsigma_2, \dots, \varsigma_I)'$, with $\boldsymbol{\varsigma} \sim MVN_I(\mathbf{0}_I, \mathbf{IDEN}_I)$. Note, however, that because of the stochasticity of the latent constructs that affect the utilities of alternatives, the overall utilities are both non-independent and non-identical across alternatives. When introducing alternative-specific constants and exogenous variables that do not vary across alternatives, the usual identification restriction is imposed such that one of the alternatives serves as the base (although this base alternative may vary for different exogenous variables). To proceed further, define the $(I \times 1)$ vector $\mathbf{U} = (U_1, U_2, \dots, U_I)'$, the $(I \times A)$ matrix $\mathbf{b} = (\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_{I_h})'$, and the $\left(\left(\sum_{i=1}^I N_i \right) \times L \right)$ matrix $\boldsymbol{\beta} = (\boldsymbol{\beta}'_1, \boldsymbol{\beta}'_2, \dots, \boldsymbol{\beta}'_I)'$. Also, define the $\left(I \times \left(\sum_{i=1}^I N_i \right) \right)$ matrix $\boldsymbol{\mathcal{G}}$, which is initially filled with all zero values. Then, position the $(1 \times N_1)$ row vector $\mathcal{G}'_1$ in the first row of $\boldsymbol{\mathcal{G}}$ to occupy columns 1 to N_1 , position the $(1 \times N_2)$ row vector $\mathcal{G}'_2$ in the second row of $\boldsymbol{\mathcal{G}}$ to occupy columns $(N_1 + 1)$ to $(N_1 + N_2)$, and so on, until the $(1 \times N_I)$ row vector $\mathcal{G}'_I$ is appropriately positioned in the final row of $\boldsymbol{\mathcal{G}}$. Further, define the $(I \times L)$ matrix $\boldsymbol{\varpi} = (\boldsymbol{\mathcal{G}}\boldsymbol{\beta})$. Then, in matrix form, we may write Equation (5) as:

$$\mathbf{U} = \mathbf{b}\mathbf{x} + \boldsymbol{\varpi} \mathbf{z}^* + \boldsymbol{\varsigma} \quad (6)$$

Thus, the components of the model framework may be written compactly with the vector equation for the latent constructs (Equation (2)) constituting the structural equation system and the vector equation for the ordinal indicators and outcomes (Equation (4)) along with the vector equation for the ranked outcomes (Equation (6)) constituting the measurement equation system.

Finally, we consider the correlations between the four latent constructs and the main outcomes. That is, we consider $\boldsymbol{\eta}$ to be correlated with both $\tilde{\boldsymbol{\epsilon}}$ and $\boldsymbol{\varsigma}$, but continue to maintain the independence assumption between $\tilde{\boldsymbol{\epsilon}}$ and $\boldsymbol{\varsigma}$. Let the $(L \times N)$ matrix $\boldsymbol{\Omega}_{\text{LN}}$ contain the correlation elements between each of the stochastic latent constructs and ordinal outcomes, and let the $(L \times I)$ matrix $\boldsymbol{\Omega}_{\text{LI}}$ contain the correlation elements between each of the stochastic latent constructs and the alternatives of the rank-ordered outcome in differenced form (see the two-headed arrows connecting the latent constructs and main outcomes in Figure 2).

To develop the reduced form equations for the GHDM modeling system, replace $\mathbf{z}^*$ in Equations (4) and (6) with the right side of Equation (2) to obtain the following system:

$$\tilde{y}^* = \tilde{\gamma}x + \tilde{d}z^* + \tilde{\varepsilon} = \tilde{\gamma}x + \tilde{d}(aw + \eta) + \tilde{\varepsilon} = \tilde{\gamma}x + \tilde{d}aw + \tilde{d}\eta + \tilde{\varepsilon} \quad (7)$$

$$U = bx + \varpi z^* + \varsigma = bx + \varpi(aw + \eta) + \varsigma = bx + \varpi aw + \varpi \eta + \varsigma$$

Now, consider the $((N+I) \times 1)$ vector of ordinal and ranked outcomes (including the indicators for the

latent constructs) $yU = \begin{bmatrix} \tilde{y}^* \\ U \end{bmatrix}$. Define

$$B = \begin{bmatrix} \tilde{\gamma}x + \tilde{d}aw \\ bx + \varpi aw \end{bmatrix} \text{ and } \Omega = \begin{bmatrix} \tilde{d}\Gamma\tilde{d}' + IDEN_N + \tilde{d}\Omega_{LN} + \Omega'_{LN}\tilde{d}' & \tilde{d}\Gamma\varpi' + \tilde{d}\Omega_{LH} + \Omega'_{LN}\varpi' \\ \varpi\Gamma\tilde{d}' + \varpi\Omega_{LN} + \Omega'_{LH}\tilde{d}' & \varpi\Gamma\varpi' + IDEN_I + \varpi\Omega_{LH} + \Omega'_{LH}\varpi' \end{bmatrix}.$$

Then the multivariate joint distribution of the main outcomes and indicators of the latent constructs is $yU \sim MVN_{N+\tilde{G}}(B, \Omega)$.

Sufficient conditions for identification are the same as those listed in Section 3.3 of Bhat and Mondal (2022). These are many and we refer the reader to Bhat and Mondal. Basically, the way we are able to identify the correlations between the latent construct themselves and the main endogenous outcomes (EV adoption and EV motivating factors) is by requiring that the latent constructs are identified solely and entirely based on the indicators without depending on the endogenous outcomes themselves as indicators. For this, given we have more than one latent construct in our model system, a sufficient condition is that, for each latent construct, there are at least two indicator variables (not considering the endogenous outcomes) that load only on that latent construct and no other latent construct (that is, there are at least two factor complexity one indicator variables for each latent construct; see Reilly and O'Brien, 1996; note also that, as indicated earlier, for the indicator variables, there are no exogenous variables on the right side of Equation (3)). In our case, we have three indicator variables loading solely on each latent construct, providing for additional stability. Further, there should not be any correlation between the error terms underlying the two indicator variables and the error term of the latent construct on which they load. Much improved stability is obtained by having all correlations between the indicator variables and the latent constructs restrained to zero (as we maintain in our analysis) as well as having variables that affect each latent construct but not the endogenous outcomes that the latent construct impacts.

3.4 Model Estimation

For model estimation, define a contrast matrix $\mathbf{M}_I$ for the ranked outcome. Specifically, define a contrast matrix based on the observed ranking r of alternatives (the contrast matrix $\mathbf{M}_I$ will vary across individuals because different individuals will rank alternatives differently; however, here we again suppress the index for individuals and develop the construction of the contrast matrix for a specific individual with a specific ranking of the alternatives). Let the first ranked alternative of the ranked outcome be r^1 , the second r^2 , and so on until the last-ranked alternative r^k , where k ($k \leq I$) is the lowest-ranked alternative selected by the participant (in our empirical case, $k \leq 3$ since each participant ranked at most three alternatives). Then, the following $(k-1)$ inequalities should hold: $U_{r^2} - U_{r^1} < 0, U_{r^3} - U_{r^2} < 0, \dots, U_{r^k} - U_{r^{k-1}} < 0$, and the following $(I-k)$ inequalities should hold: $U_{r^{k+1}} - U_{r^k} < 0, U_{r^{k+2}} - U_{r^k} < 0, \dots, U_{r^I} - U_{r^k} < 0$. Stack the $(I-1)$ utility differentials above, ordered as above based on the observed rank ordering, into a vector

$$\mathbf{u} = \left((U_{r^2} - U_{r^1}), (U_{r^3} - U_{r^2}), \dots, (U_{r^k} - U_{r^{k-1}}), (U_{r^{k+1}} - U_{r^k}), (U_{r^{k+2}} - U_{r^{k+1}}), \dots, (U_{r^I} - U_{r^k}) \right)'. \quad \text{Also,}$$

define the $((N+I-1) \times 1)$ vector $\mathbf{y}\mathbf{u} = \begin{bmatrix} \tilde{\mathbf{y}}^* \\ \mathbf{u} \end{bmatrix}$.

In vector notation, we can write the inequalities using a contrast matrix $\mathbf{M}_I$ with $(I-1)$ rows for each inequality and I columns for each alternative. To start, fill all the elements of the contrast matrix with zeros. Then, starting with the first row, place a value of negative one in the column corresponding to the first-ranked alternative, and a value of one in the column corresponding to the second-ranked alternative (this row corresponds to the first inequality shown above). Moving to the second row, place a value of negative one in the column corresponding to the second-ranked alternative, and a value of one in the column corresponding to the third-ranked alternative (this row corresponds to the second inequality shown above). Continue this procedure for each row, until placing a value of negative one in the column corresponding to the k^{th} alternative, and a value of one in the column corresponding to the final unranked alternative (corresponding to the last inequality above).

Then, define a larger matrix $\mathbf{M}$ of size $((N+I-1) \times (N+I))$, initially filled with zeros. For the ordinal outcomes, place an identity matrix of size $(N \times N)$ into the first N rows and N columns of matrix $\mathbf{M}$. Then for the ranked outcome, place the contrast matrix $\mathbf{M}_I$ in rows $N+1$ to $N+I-1$ and columns $N+1$ to $N+I$. Thus, in the case of $N=2$ and $I=4$, if the individual's ranking for two ranked outcomes (from the top choice to the last choice) is $4 > 1$ (with alternatives 2 and 3 unranked), then the $\mathbf{M}$ matrix for this individual is as below:

$$\mathbf{M} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & -1 \\ 0 & 0 & -1 & 1 & 0 & 0 \\ 0 & 0 & -1 & 0 & 1 & 0 \end{bmatrix}.$$

Using the contrast matrix $\mathbf{M}$, we can develop the distribution of the vector $\mathbf{y}\mathbf{u}$ from that of $\mathbf{y}\mathbf{U}$ because $\mathbf{y}\mathbf{u} = \mathbf{M}(\mathbf{y}\mathbf{U})$. Specifically, $\mathbf{y}\mathbf{u} \sim MVN_{N+I-1}(\tilde{\mathbf{B}}, \tilde{\mathbf{\Omega}})$, where $\tilde{\mathbf{B}} = \mathbf{M}\mathbf{B}$, $\tilde{\mathbf{\Omega}} = \mathbf{M}\mathbf{\Omega}\mathbf{M}'$.

Next, define the two $((N+I-1) \times 1)$ threshold vectors $\tilde{\boldsymbol{\psi}}_{low} = \begin{pmatrix} \tilde{\boldsymbol{\psi}}_{low} \\ -\infty_{I-1} \end{pmatrix}$ and $\tilde{\boldsymbol{\psi}}_{up} = \begin{pmatrix} \tilde{\boldsymbol{\psi}}_{up} \\ \mathbf{0}_{I-1} \end{pmatrix}$, where $-\infty_{I-1}$ represents a $((I-1) \times 1)$ column vector of negative infinities, and $\mathbf{0}_{I-1}$ represents a $((I-1) \times 1)$ column vector of zeros. Collect the set of parameters to be estimated into the vector $\boldsymbol{\delta} = [\text{Vech}(\boldsymbol{\alpha}), \text{Vechup}(\boldsymbol{\Gamma}), \text{Vech}(\tilde{\boldsymbol{\gamma}}), \text{Vech}(\tilde{\boldsymbol{d}}), \tilde{\boldsymbol{\psi}}, \text{Vech}(\mathbf{b}), \boldsymbol{\vartheta}, \text{Vechup}(\boldsymbol{\Omega}_{LN}), \text{Vechup}(\boldsymbol{\Omega}_{LH})]$, where the operator $\text{Vech}(\cdot)$ vectorizes all the non-zero elements of the matrix/vector on which it operates and $\text{Vechup}(\cdot)$ vectorizes all the non-zero upper diagonal elements. Then the individual-level likelihood function may be written as:

$$L(\boldsymbol{\delta}) = \Pr \left[\tilde{\boldsymbol{\psi}}_{low} \leq \mathbf{y}\mathbf{u} \leq \tilde{\boldsymbol{\psi}}_{up} \right] = \int_{D_r} f_{N+I-1}(\mathbf{r} \mid \tilde{\mathbf{B}}, \tilde{\mathbf{\Omega}}) d\mathbf{r} \quad (8)$$

where the integration domain $D_r = \{\mathbf{r} : \tilde{\boldsymbol{\psi}}_{low} \leq \mathbf{r} \leq \tilde{\boldsymbol{\psi}}_{up}\}$ is the multivariate region of the elements of the $\mathbf{y}\mathbf{u}$ vector determined by the observed ordinal outcomes, and the range $(-\infty_{I-1}, \mathbf{0}_{I-1})$ for the utility differences taken with respect to the utility of the ranked preference for the rank-ordered outcome. The

likelihood function for the entire sample of decision-makers is obtained as the product of the individual-level likelihood functions.

The likelihood function shown in Equation (8) involves the evaluation of an $(N + I - 1)$ dimensional integral for each decision-maker. Given that this calculation is computationally expensive, we evaluate this integral using Bhat's (2018) matrix-based approximation method for evaluating the multivariate normal cumulative distribution function.

4. RESULTS AND DISCUSSION

The final model specification is based on an iterative process of including exogenous variables in various forms and testing alternative combinations of exogenous variables based on statistical fit. Categorical variables included in the model were considered in the most disaggregate form available and iteratively combined to yield parsimonious specifications based on statistical tests. Additionally, several continuous variables were tested in various forms, but the best representation in each case was in the form of dummy variables (for instance, population density was best captured as a single dummy variable indicating whether the respondent lived in an area with a density above the population weighted average density of all zip codes in the state). In the model estimation process, we used a t-statistic threshold of 1.65 (corresponding to a 0.1 level of significance or 90% confidence level) to retain variables for the EV ownership dimension and SEM model component. Due to the limited number of EV owners with a ranked set of factors motivating adoption, a lower t-statistic threshold of 1.28 (corresponding to a 0.2 level of significance or 80% confidence level) was used to retain variables impacting these ranked outcomes.⁵ The final estimation results are shown in Table 3 and Table 4. A “—” entry in the results tables indicates that the row exogenous variable does not have any statistically significant impact on the column latent construct (for Table 3) and endogenous outcome (for Table 4).

The results are organized into several sections. Section 4.1 presents the results of the effects of exogenous variables on the four latent constructs (constituting the SEM component of the model) as well as the loadings of the latent constructs on the set of indicators (constituting part of the MEM component of the model). The results of the MEM model component corresponding to the effects of exogenous variables and latent constructs on the main endogenous outcomes are presented in Section 4.2. Then, Section 4.3 discusses the model fit in relation to a restricted GHDM model that does not consider the correlations between the stochastic latent constructs and the main outcomes and an independent model that ignores all jointness among the outcomes. Finally, Section 4.4 presents the approach used to compute the effect-sizes of each exogenous variable on EV adoption.

4.1 Latent Constructs

Table 3 displays the results for the determinants of the four latent constructs. All the explanations of the results in this section and beyond refer to general tendencies, rather than absolute statements.

The results of the SEM model component (shown in the upper panel of Table 3) reveal that gender impacts green lifestyle propensity (GLP), vehicle functionality preference (VFP), and cost and maintenance

⁵Several important considerations underlie our use of an 80% confidence level for variables impacting the ranked adoption motivation outcome. In empirical modeling situations, analysis must balance concerns regarding Type I errors (falsely attributing significance to irrelevant variables) and Type II errors (rejecting variables incorrectly and overlooking meaningful relationships). Selecting a confidence level inherently involves a tradeoff between these risks. As emphasized by the American Statistical Association (ASA) (see Wasserstein and Lazar, 2016; Wasserstein et al., 2019), researchers must exercise context-specific judgements about the appropriate thresholds to use in any empirical application rather than adhering rigidly to the typically used 95% level of confidence (or 0.05 level of significance). In our current application, with a relatively modest sample size and particularly limited number of respondents with a full set of ranked outcomes for the motivating reasons for EV adoption, we prioritized reducing the probability of Type II errors compared with a standard 0.05 level of significance. This allows us to identify variables that still seem to be relatively significant in our current dataset and help inform future specifications using larger samples, and particularly larger samples of actual EV owners, even if this allows for a slightly higher probability of a Type I error.

perception (CMP). The gender influence on GLP is well documented in existing literature, as women exhibit a greater overall inclination toward environmental awareness and sustainable behaviors (see Anfinssen et al., 2019; Bloodhart and Swim, 2020). Women also tend to view vehicles more in terms of functionality, while men are more likely to see them as status symbols, which would explain the positive impact of identifying as female on VFP. Indeed, earlier literature indicates that women are more interested in the mobility control provided by vehicle ownership, while men associate vehicle ownership with technological interest, self-identity considerations, and driving enjoyment. This difference itself has been associated with financial disparities and gendered mobility roles that historically have led to lower level of mobility among women compared with men (Kawgan-Kagan, 2020), leading to a greater interest in mobility control and vehicle functionality among women (Hjorthol, 2008). In contrast, men are more likely to take vehicle ownership for granted and focus on the specific interests in technology innovation and public image when considering vehicles, associating vehicles with societal expectations of masculinity (Sovacool et al., 2019). The gender effect on CMP, which suggests that men are more likely to perceive EVs to be cost effective and easy to maintain, may again relate to the greater feelings of financial autonomy among men, as they exhibit less concern with initial purchase price (Egbue and Long, 2012), as well as a greater interest in, and greater awareness of the relative maintenance requirements of, EVs and ICEVs (Sovacool et al., 2019; Jia and Chen, 2021).

Age impacts VFP and battery range and charging perception (BRP), with older adults viewing vehicles as primarily functional, while also being less convinced than younger adults about the suitability of EVs for long-distance trips. The first result is consistent with literature suggesting that younger adults enjoy driving more and are strongly motivated by symbolic and affective concerns, while older adults focus more directly on the mobility provided by vehicle ownership and the functional aspects of the vehicle such as safety and fuel efficiency (Steg, 2005; Koppel et al., 2013). The second finding relates to a lower level of trust for new technologies among older adults. While older individuals tend to be slower to adopt new technologies because of a lower overall level of technology savviness (Berkowsky et al., 2017; Pang et al., 2021), this finding may also reflect the higher risk aversion among older adults, which has been shown in the case of EVs to cause them to perceive range and charging concerns to be a bigger barrier than it is for younger individuals (Jin et al., 2024). Relatedly, retired individuals, compared with employed individuals also have a higher CMP, likely because they generally feel a greater sense of financial freedom (particularly in early retirement), have more financial literacy than younger adults, and have the resources to make large up-front investments for purchases like vehicles (Collins and Urban, 2020).

In contrast to the findings of several recent studies suggesting that Hispanic individuals exhibit higher levels of pro-environmental behaviors (see Macias, 2016; Pearson et al., 2018; Naiman et al., 2023), we find that Hispanic individuals exhibit a lower GLP compared with non-Hispanic individuals. This result is likely due to the framing of the indicators in terms of “personal obligation” and “guilt” which are likely to align with the motivations of non-Hispanic white individuals rather than collectivist values of environmental justice which are more likely to motivate Hispanic individuals (see Naiman et al., 2023). Further, the type of environmentally conscious attitude more common to Hispanic individuals seems to be aligned more towards routine pro-environmental practices as well as a focus on the connections with other interrelated social issues, rather than larger symbolic actions (such as EV ownership) that are more directly aligned with an individualistic-oriented environmental preference and signaling (Tam and Chan, 2017; Liu and Segev, 2017; Naiman et al., 2023). Hispanic individuals also exhibit a higher VFP, a focus on vehicle functionality that is aligned with the values of collectivism. Regarding cost perceptions, Hispanic individuals have a lower CMP overall, supporting existing evidence that Hispanic individuals place a lower valuation on the cost to fuel or charge their vehicle and even more so on the cost to maintain the vehicle, while, at the same time, ascribing a higher valuation on initial purchase price (see Findley et al., 2022). Finally, Hispanic individuals, as well as non-white individuals manifest more positive perceptions of EV range. This result is surprising, given that Black and Hispanic individuals generally have less access to EV chargers compared with non-Hispanic white individuals (Hsu and Fingerman, 2021). However, there is evidence that these populations are more likely to develop fixed charging routines (particularly for charging at the workplace), take greater numbers of short urban trips, and exhibit more adaptability to charging

options, each of which provides increased range security (Chen et al., 2024; Lou et al., 2024). These results highlight the importance of considering charging perceptions alongside physical access to charging infrastructure, as the need for charging infrastructure varies according to intended use.

In terms of educational attainment, individuals with a higher level of formal education tend to have an elevated GLP, presumably because those with more formal education are more aware of the negative consequences of environmentally harmful actions (see Liu et al., 2020). Those with higher formal levels of educational attainment also have a more positive perception of EV technologies in terms of both cost and maintenance requirements and battery and charging technologies, perhaps because these individuals are likely to have specific knowledge of EV features as well as to maintain an increased awareness of their own spending habits, making EVs seem like a more feasible alternative (Memushi, 2014; Habich-Sobieggalla et al., 2019). Similar results hold for income, with individuals living in high-income (greater than \$200,000 per year) households having a higher GLP, concordant with Maslow's (1943) hierarchy of needs that short-term existential needs precede longer-term planetary livability considerations. Further, while EVs can provide long-term financial benefits, those with higher incomes are better able to afford the higher initial purchase prices, explaining the positive influence of income on CMP (see, for example, Ramos-Real et al., 2018).

Those living in multifamily units or apartments (relative to those living in single-family homes), and those in areas with higher EV charging station density, have higher positive perceptions of EV ranges and battery technology. Although those living in multifamily dwellings may have less control over charging availability in their parking spaces, there is evidence that the provision of dedicated spaces with charging access at apartment complexes may promote positive perceptions of EVs (see Lashari et al., 2021). Additionally, those living in multifamily dwellings may be more aware of the availability of local public charging stations, providing them with more confidence in using their EVs for long distance trips where home charging is unavailable (see Lee et al., 2020). Similarly, the availability of EV charging stations in a respondent's neighborhood promotes a positive perception of range capabilities, consistent with many existing studies (see, for example, White et al., 2022; Pandita et al., 2024).

The central panel of Table 3 includes the loadings of the latent constructs on the indicator variables, corresponding to the MEM model component. The signs on the latent constructs for all indicators take the expected sign, consistent with the discussion earlier in Section 3.1.3. The lower panel of Table 3 includes the correlations between the latent constructs (see Γ near the top of Figure 2). A small positive correlation between GLP and VFP is expected since individuals who prioritize sustainable behaviors will likely also prioritize vehicle performance over status effects. Stronger positive correlations exist among GLP, CMP, and BRP; that is, those with more interest in sustainability are likely to seek out more information about EVs, which generally improves perceptions of maintenance requirements and range (see R. Liu et al., 2020). The high correlation between CMP and BRP may also be due in part to the co-location of EV charging infrastructure and EV financial incentives, leading individuals living in specific areas to have more positive views of each of these features of EVs (for instance, residents of the San Francisco Bay Area have greater access to local public charging stations than those in many of the surrounding areas and have access to additional financial incentives for EV purchases through the Clean Cars for All program; Bay Area Air Quality Management District, 2023). Finally, smaller positive correlations between VFP and CMP as well as between VFP and BRP likely relate to the knowledge about EVs and EV infrastructure stemming from a greater interest in EVs and the various aspects of EV functionality.

4.2 Main Estimation

Table 4 presents the estimation results for the main outcome dimensions. The coefficients refer to the impact of each variable on the underlying utilities for each alternative. The constants in the first row of the table do not have any meaningful interpretations but are simply estimated to match the observed choice proportions (for the adoption dimension) and ranked proportions (for the ranked adoption reasons).

4.2.1 Effects of Latent Constructs

As expected, individuals with a high GLP are more likely to buy an EV overall and do so because of concerns regarding climate change, while those with low GLP are less likely to buy an EV but more likely to cite the ability to take advantage of available incentives as a reason for adoption. These effects are even stronger for older individuals and those from higher income households (see the two graphs on the left side of Figure 3, which show the average probability of EV adoption given an individual's age/income and level of GLP). These individuals are better able to act on their green lifestyle preferences because they are at a life stage where they have the financial wherewithal to afford the high up-front purchase cost. In contrast, younger individuals and those from lower-income households may not be as influenced by their level of GLP because they tend to actualize environmental preferences through other less financially burdensome means rather than through investments in sustainable technologies (similar tendencies have been demonstrated for other types of environmental practices, such as energy conservation practices; see Brunner et al., 2012; Liu et al., 2019).

Those with a high vehicle functionality preference or VFP (who emphasize functionality over status) seem less likely to buy a BEV overall, presumably because they do not yet see BEVs as being functionally competitive with ICEVs. However, this result does not seem to hold for PHEV adoption. VFP does not seem to have a large effect on PHEV adoption, possibly because PHEVs may be viewed as more functionally competitive overall with ICEVs, as they provide more flexibility in charging/fueling, while retaining much of the symbolic appeal of BEVs. Individuals with high VFP appear to be drawn toward EVs (in general) because of the ability to charge at home (which provides temporal and monetary benefits compared with public fueling needed for ICEVs) and the ability to take advantage of incentives. In contrast, those who view vehicles as a status symbol (low VFP) are drawn toward EVs because of interest in a specific brand or model that bring with them a perceived social status boost. The impact of VFP on the utility of EV adoption is stronger for older individuals; that is, for those with the same level of VFP, older individuals are less likely to adopt EVs relative to their younger peers (see the top-right graph in Figure 3, which shows the average probability of EV adoption given an individual's age and level of VFP). As will be discussed later, we did not find any direct effect of age on EV adoption in this sample; any effect of age on EV adoption is solely through its interplay with vehicle functionality versus vehicle status perceptions. Thus, between a younger and older individual, both of whom emphasize functionality (high VFP), older individuals are more likely to stay away from EV adoption, potentially because of inertia in moving away from the ICEV vehicles they have driven for a long period of time (corresponding to their driving lifespan). However, there is less of a difference between younger and older individuals in their EV adoption tendency for those who view EVs as a status symbol (low VFP). A similar interaction effect is observed with respect to income (see the bottom-right graph in Figure 3, which shows the average probability of EV adoption given an individual's income and level of VFP), with individuals from high-income households with a high VFP being much more unlikely to adopt EVs relative to their low-income peers with a similar high VFP, while income differences play much less of a role in EV adoption among individuals who place substantial weight on EV prestige/status considerations (low VFP). This finding highlights the successes that EV companies have had in directing their information campaigns to consumers based more on the status and prestige (rather than cost/functionality) afforded by owning an EV (see Noel et al., 2019). In essence, individuals who view EVs as primarily a status symbol are uniformly more likely to adopt EVs, regardless of age and income. In contrast, households with children are uniformly more likely to buy EVs if they consider the primary purpose of the vehicle to be functional, highlighting the need for manufacturers to emphasize the practical benefits of EVs to better connect with market segments focused primarily on functionality.

Our analysis also reveals significant impacts of EV perceptions, as both cost and maintenance perception (CMP) and battery range and charging perception (BRP) impact the utility of adoption. Those who perceive EVs to be more cost effective and easier to maintain relative to ICEVs (high CMP) are more likely to be adopters and are attracted to EVs for economic reasons (including rising gas prices and the ability to take advantage of incentives, though, expectedly less so for individuals from high-income households relative to those from lower-income households), as well as interest in the technology and ability

to charge at home. The overall effect of CMP on EV adoption is even stronger for PHEVs relative to BEVs. This may be because PHEVs are more similar to traditional ICEVs, so that cost-effectiveness matters more for PHEV acceptance. Families with children also place much more of a premium on CMP in their EV adoption propensity relative to families without children, suggesting that any awareness campaigns with an EV cost-effectiveness and hassle-free maintenance emphasis would be more effective if directed toward families with children. Finally, those with positive perceptions of EV battery technology and range (high BRP) are more likely to adopt EVs. The main motivating factors for such individuals in terms of draw toward EVs is personal experience through test drives and because they heard about EVs from family members or friends. This result suggests that experience with EV technology may serve as an important tool to alleviate range anxiety, possibly providing familiarity with EV range and knowledge of charging stations that helps to ease these concerns (Rauh et al., 2015). These individuals are also more likely to cite interest in a specific brand or model, likely because charging availability is impacted significantly by EV brand and the types of charging stations that are available in different areas, leading to an interest in specific EV brands with higher charging availability (Haustein et al., 2021). The effects of BRP on EV adoption are stronger for those living in multifamily (attached) homes or apartments. This is an intuitive result given that these families generally have fewer home charging options, so may be more reliant on (and thus, more influenced by the availability of) public charging infrastructure (Lee et al., 2020; Kuby et al., 2024).

A general note is in order here about the effects of demographics. The effects of gender and age on EV adoption are through their interaction effects with latent constructs, rather than as direct effects (see the next section). On the other hand, many studies that consider attitudes/lifestyles in the form of latent constructs introduce such constructs purely as main effects on the outcomes of interest. Our results suggest the importance of exploring interaction effects of latent constructs with individual/household-level variables, as also discussed at length in Bhat and Mondal (2022).

4.2.2 Effects of Individual Demographics

The effects of the exogenous variables shown in Table 4 provide the direct effects of the variables, beyond the indirect effects through the latent constructs. After accounting for the indirect effects, we find no additional difference in overall propensity to purchase EVs between men and women. However, men, in general, are drawn toward EVs because of interest in the technology and the ability to charge at home, consistent with the EV literature (Wang et al., 2021; Salari, 2022). Similarly, after accounting for the latent construct effects and interactions, there is no direct effect of age on EV adoption. However, older individuals are more drawn to EVs (relative to their younger peers) due to government incentives for EV purchase, interest in a specific brand, and positive test-drive experiences. These findings align with consumer research suggesting that older consumers may be more responsive to policy incentives and brand loyalty in their vehicle choices (Mittal and Kamakura, 2001; Jørgensen et al., 2016).

Non-white and Hispanic individuals have a lower propensity to buy EVs overall, although there are no significant differences among these groups in the factors that motivate EV adoption in the first place (after accounting for the differential effects through the latent constructs). The disparity in EV adoption may be a result, at least in part, of (a) marketing strategies of EV companies, which have primarily focused on white male demographics, and (b) generally lower level of technology uptake by minority populations due to lower levels of technology awareness, itself associated with the relatively sparse knowledge networks among minority groups (Warschauer et al., 2004; Hsu and Fingerman, 2021). For similar reasons, those with lower levels of formal educational attainment also appear less inclined to adopt EVs, even after accounting for differences through the latent constructs.

4.2.3 Effects of Household Demographics and Location

Among household characteristics, single adult households adopt EVs less than multi-adult households and invoke the ability to charge at home and hearing about EVs from friends and family as adoption motivators. Larger families, in contrast, are likely to be attracted to EVs due to purchase incentives. In addition, the presence of children in the household positively influences adoption, although this seems to be primarily for adoption of PHEVs, which provide more flexibility in terms of charging/fueling, an issue that is likely

to be particularly important for families with children. Both households with 2+ adults and those with more children also tend to have more vehicles in general to accommodate the transportation needs of more household members, making it easier to include an electric vehicle in the mix (Chen et al., 2015; Munshi et al., 2022). In addition, this finding may reflect a more recent trend of EV models being designed with larger families in mind (Higgins et al., 2017; Lučić et al., 2024).

Although many stated preference surveys have found that income has a moderate impact on EV adoption, primarily due to sensitivity to initial purchase price (see Ramos-Real et al., 2018; Xue et al., 2021; He et al., 2022; Yang et al., 2023; Pandita et al., 2024), other findings are mixed (see Helveston et al., 2015; Ferguson et al., 2018). We find a significant positive effect of household income on EV adoption, even after accounting for effects through the latent constructs. Individuals from high-income households are particularly motivated by interest in specific brands or models of EVs, experience, and social influence. This finding highlights the successes of EV manufacturers in marketing luxury EVs to high-income segments. In contrast, individuals from low-income households cite rising gas prices as the main motivator for considering EVs.

A negative direct effect between living in a multifamily dwelling and BEV adoption, as revealed in Table 4, moderates the positive effect of housing type on EV adoption through BRP (the indirect effect, calculated as $(0.53 + 0.99) \times 0.28 = 0.43$, is moderated by the direct effect of -0.46). Essentially, while those living in multifamily homes or apartments are more likely to adopt EVs (in general) because they have more positive perceptions of out-of-home charging and EV range, they seem to be just as likely to adopt BEVs overall as those living in single-family (detached) homes. However, those living in apartments or multifamily dwellings seem more likely to adopt PHEVs compared with those living in single family homes (as a positive interaction between PHEVs essentially negates the overall direct housing type effect, leaving only the indirect effect through BRP). Those living in multifamily dwellings are also less likely to cite home charging as a reason for adoption, an unsurprising result given the lack of control of charging infrastructure for these dwellings.

Household location also significantly influences EV adoption. Those living in high density areas are more likely to adopt EVs and are attracted to EVs for economic reasons and greater concerns of climate change, while those living in lower-density areas are drawn to EVs because of the ability to charge at home. These different motivations for adoption in different areas may be traced to higher gas prices in urban areas and the higher ability to own homes in rural areas (Mukherjee and Ryan, 2020; Chandra, 2022). Finally, individuals living in areas with high charging densities are also more likely to adopt EVs. The fact that these individuals also report that hearing about EVs from friends and family attracts them to EVs suggests that improving charging infrastructure may also be an important way to increase awareness about EVs, beyond the direct impacts on actual charging abilities (see Bailey et al., 2015).

4.2.4 Correlations Between Main Outcomes and Latent Constructs

In addition to the correlations among the stochastic latent constructs (discussed in Section 4.1) and the correlations among the main outcomes engendered by the latent constructs, we consider the latent constructs themselves to be endogenous with the main outcomes. Six of these correlation terms turn out to be significant. EV ownership is positively correlated with GLP (correlation of 0.13 with a t-statistic of 1.92), suggesting that additional unobserved factors influence both EV ownership and green lifestyle preferences. Positive correlations are also found between EV ownership and CMP (correlation of 0.19 with a t-statistic of 2.62) as well as between EV ownership and BRP (correlation of 0.11 with a t-statistic of 2.80). These positive correlations indicate that intrinsic factors, such as interest in technology, may not only influence how individuals perceive specific EV characteristics, but their overall propensity for adoption as well. Since each of these correlations between the latent constructs and the EV ownership dimension match the signs of the direct effects, the implication is that if they were ignored in estimation, the magnitude of the direct effects would be overestimated. Three correlation terms between the stochastic latent constructs and the error differences in the ranked motivating reasons outcome are also significant. For the rank-ordered outcome only error differences are estimable, so the correlations are estimated for the errors differenced with “rising gas prices.” We observe positive correlations between VFP and with both the “ability to charge

at home” (correlation of 0.22 with a t-statistic of 1.81) and “take advantage of available incentives” (correlation of 0.25 with a t-statistic of 1.44). This suggests that underlying attitudes lead some individuals, such as those with higher interest in consumer innovation, to focus more on vehicle functionality (as they have higher performance expectations) while also prioritizing being able to charge at home or take advantage of incentives in their purchase decision (as they are more likely to have high appreciation for these specific features and seek out information about available government support). Ignoring this correlation would lead to overestimation of the effects of VFP on these specific motivating reasons. The final significant correlation is between GLP and the error term for “take advantage of incentives” (correlation of 0.19 with a t-statistic of 1.97). This correlation indicates that unobserved factors influence both sustainability preferences and the ability to take advantage of financial incentives, possibly linked to differential access to incentives based on location and self-selection effects that tend to lead people to co-locate based, in part, on lifestyle preferences, like those for sustainability (see Guan et al., 2020; Chakraborty et al., 2022).

4.3 Model Fit

To assess the overall fit of the proposed joint GHDM model, it is compared with two restricted models. First, while the significant correlations between the stochastic latent constructs and the main outcomes (discussed in Section 4.2.4) already point to the need to consider these correlation terms, the proposed GHDM is compared with another GHDM model that ignores the correlations between the stochastic latent constructs and the main outcomes. Several disaggregate fit metrics are used to compare these models as shown in the top panel of Table 5. The Bayesian Information Criterion (BIC) is calculated as

$$BIC = -\mathcal{Z}(\hat{\theta}) + 0.5(\# \text{ of model parameters}) \log(\text{sample size}) \quad (9)$$

where $\mathcal{Z}(\hat{\theta})$ represents the log-likelihood at convergence and the adjusted likelihood ratio index is calculated as

$$\bar{\rho}^2 = 1 - \frac{\mathcal{Z}(\hat{\theta}) - M}{\mathcal{Z}(c)} \quad (10)$$

where $\mathcal{Z}(c)$ represents the log-likelihood for the constants-only model and M is the total number of parameters (excluding constants) estimated in the model. Since the BIC is lower for the proposed GHDM and the adjusted likelihood ratio index is higher for the proposed GHDM than the GHDM model that ignores the correlations, it is the preferred model. Further, since the restricted GHDM without correlations between the latent constructs and main outcomes is a nested version of the proposed GHDM, the two can be compared with a formal likelihood ratio test using the log-likelihood at convergence for each of the two models. The likelihood ratio test statistic is greater than the chi-square value with six degrees of freedom at any reasonable level of significance.

Second, the predictive power of the proposed GHDM model can be assessed by comparing a similar set of metrics based only on the prediction of the main outcomes. The proposed model is compared again with the GHDM model that ignores the correlations between the latent constructs and the main outcomes, as well as with a restricted independent heterogeneous data model (IHDM) that ignores any jointness between the main outcomes (does not consider any correlation between the main outcomes in the model). As jointness in the GHDM is engendered through the stochastic latent constructs, the IHDM model ignores the latent constructs (and the interactions of the latent constructs with individuals/household demographics). Thus, for this comparison, we evaluate the predictive log-likelihood solely for the EV adoption and ranked adoption motivation dimensions using the complete set of coefficients for the GHDM model. Then, for the IHDM, we estimate an independent model for the same main outcomes, without the inclusion of the latent constructs but including the determinants of the latent constructs as exogenous variables in the main outcome equations.

For these models, the Bayesian Information Criterion (BIC) calculated using the predictive log-likelihood is lowest for the proposed GHDM model while the predictive adjusted likelihood ratio index is

highest for the proposed GHDM model. Then, comparing the proposed GHDM and the GHDM that ignores correlations between the latent constructs and main outcomes using an informal predictive likelihood ratio test again favors the proposed GHDM model. Since the IHDM is not a nested model (as the IHDM lacks a mechanism to incorporate latent constructs), the informal predictive non-nested likelihood ratio test is used to compare the proposed GHDM and the IHDM. For this test, the probability that the difference between the predictive adjusted likelihood ratio index for the GHDM model ($\bar{\rho}_{GHDM}^2$) and the index for the IHDM model ($\bar{\rho}_{IHDM}^2$) could have occurred by chance is no larger than

$$\Phi\{-[-2(\bar{\rho}_{GHDM}^2 - \bar{\rho}_{Independent}^2)\mathcal{Z}(c) + (M_{GHDM} - M_{Independent})]^{0.5}\} \quad (11)$$

Given the small value of this probability for the two models, the proposed GHDM model is preferred because it has a larger value of the adjusted likelihood ratio index. Finally, the three models can be compared informally by computing the average (across individuals) probability of correctly predicting the observed EV adoption outcome and set of motivating reasons for adoption (where appropriate). The average probability of a correct prediction at this two-variate level is higher for the proposed GHDM model than either restricted model, again demonstrating the superior fit of the GHDM model in comparison with either restricted model.

In addition to the disaggregate measures, the three models can be compared based on their aggregate fit. The bottom panel of Table 5 shows the observed (weighted) and predicted (using each of the three models) shares of individuals adopting EVs and selecting each of the motivating reasons for adoption as their top-ranked choice. Then, in each case, the absolute percentage error is calculated based on the difference between the observed and predicted shares, and an average of the absolute percentage errors for each factor is taken, weighted by the observed share. This weighted average percent error (WAPE) is lowest for the proposed GHDM compared with both restricted models, demonstrating the higher predictive power of the proposed model. Together, these results demonstrate (at both an aggregate and disaggregate level) that the proposed GHDM model outperforms the restricted GHDM model that ignores the correlations between the latent constructs and the main outcomes as well as the IHDM model that ignores any jointness between the main outcomes themselves, confirming the importance of using the joint estimation approach.

Finally, the predictive performance of the three models is compared on various market segments of the estimation sample (Ben-Akiva and Lerman, 1985, refer to such tests as market segment prediction tests). These additional tests are performed across market segments to ensure that the performance of the joint model does not simply result from overfitting on the estimation sample. Using the same methods as the evaluation for the complete sample, the predictive power of the proposed GHDM model is compared with the GHDM model that ignores the correlations between the latent constructs and the main outcomes by evaluating the predictive log-likelihood solely for the EV adoption and ranked adoption motivations and comparing the models using an informal predictive likelihood ratio test. Similarly, the predictive power of the proposed GHDM model is compared with the IHDM model using the informal predictive non-nested likelihood ratio test, as before. Finally, at an aggregate level, the weighted average percent error (WAPE) is calculated for all three models for comparison. These data fit metrics are shown in Table 6 for 12 market segments (for each exogenous variable, the data fit for the market segment with the greatest number of observations is presented). The results in Table 6 support the superiority of the proposed GHDM model over both restricted models (based on both aggregate and disaggregate metrics) within each market segment, providing additional verification of the robust data fit of the proposed model which is not merely attributable to overfitting.

4.4 Average Treatment Effects

The main estimation results presented in Section 4.2 provide important insights into the effects of the exogenous variables on the underlying propensity associated with EV adoption and the utilities of the ranked reasons for adoption. However, these results do not provide the magnitude effect of each variable on the actual binary adoption decision or the magnitude influence that indirectly results through each of the latent constructs. For this, we use Average Treatment Effects (ATEs), which characterize the impact on an

outcome variable of a change of state of an antecedent variable. For instance, if the intent is to compute the effect of gender on EV adoption, we begin by setting the gender of all individuals in the dataset to “Male” without changing the values of any other exogenous variables. Then we compute, for each individual, the bi-variate probability predictions for each combination of EV adoption outcome and first-ranked reason for adoption (for a total of 16 combinations of outcomes). By marginalizing over the combinations, we can obtain the probability that each individual would adopt an EV for the base level of the exogenous variable (“Male”). The same procedure is adopted for the treatment level of the exogenous variable by setting the gender of all individuals in the dataset to “Female” without changing the values of any other exogenous variables and calculating the probability that each individual would adopt an EV as before. The change in the share of adopters provides the magnitude and direction of the total ATE of the “Gender” variable on EV adoption. For exogenous variables with more than two levels (such as age), we compute the ATEs for a change between only the highest and lowest levels. Essentially, these ATEs are computed using counterfactual simulations by changing variable values from the observed values.

In addition to this total ATE effect, we also partition the ATE into five sub-components based on the contributions through each of the four latent constructs and a direct effect. To compute the relative magnitude of the contributions we compute each sub-effect separately. For instance, we compute a direct effect of one exogenous variable by maintaining the values of all other exogenous variables as well as fixing the values of each of the latent constructs to those calculated as all variables are in the data. Then, for the mediating effects through the latent constructs, we maintain the values of all variables as they are in the data for the purposes of the main outcome variables but change the value of the exogenous variable of interest only in the equation for a single latent construct. To compute the relative magnitudes of the contribution of each ATE sub-component, we compute percentages of the sum of the absolute values of these sub-components (ignoring the directionality of each sub-effect). Then, the sign associated with each contribution illustrates whether the corresponding effect increases the total ATE (+) or decreases the total ATE (-).

The final ATE effects for EV adoption are shown in Table 7. The entry in the final column of the table shows the total ATE of each exogenous variable on EV adoption. For instance, the first entry of “-0.0668” for gender indicates that, in a pool of 100 women, one may expect about 7 fewer individuals to adopt EVs relative to a pool of 100 men. The five columns to the left of the “Total ATE” column provide the percentage splits of the ATE sub-components originating through each of the latent constructs and through a direct effect. For example, the total ATE for gender is attributable to an increased adoption rate among women due to a higher GLP (contributing +22%) that is surpassed by a reduced adoption rate among women due to a higher VFP (contributing -17%) and lower CMP (contributing -61%). There is no direct ATE for gender or mediating effect through BRP. In the following section, we discuss the implications of our results based on the ATE calculations shown in Table 7 combined with the reasons for EV adoption shown in Table 4.

5. IMPLICATIONS

5.1 Implications for Financial Incentives and Policies

The variables that have the largest overall ATE impact on EV adoption are level of formal educational attainment and household income. For instance, we find that in a pool of 100 “graduate degree holders” there would be approximately 34 additional EV owners compared to a pool of “less than bachelor’s degree holders,” while in a group of 100 “\$200,000 or more income” earning households there would be 23 additional EV owners compared to a group of 100 “less than \$100,000 income” earning households. Although many studies have confirmed the importance of level of education (Kim et al., 2019; Singh et al., 2020), the results of stated preference studies regarding income have been mixed. While some studies have found income to positively influence EV interests (Axsen et al., 2016; Kumar and Alok, 2020), others have found insignificant, or even negative, effects (Helveston et al., 2015; Ferguson et al., 2018). The large positive impact of income in our revealed preference dataset suggests that, even though lower income individuals may have interest in EVs, that does not currently translate into actual adoption behaviors. The importance of household income as a determinant of EV adoption may point to the early stage of the EV

market, high purchase prices of EVs, and the necessity of providing incentives that meet the needs of middle and lower-income households. Expanding the availability of incentive structures directed toward low-income consumers, which provide point-of-sale support and are specifically targeted towards lower-cost vehicles, will more effectively incentivize adoption for a broader population. At the same time, the development of a robust secondary market for EVs represents an important pathway for expanding adoption among lower-income households, who might otherwise be excluded from the EV market due to the high initial purchase price of new vehicles. Thus, strategies specifically designed to facilitate the development of a healthy used (pre-owned) EV market through mechanisms such as battery warranty programs and certified pre-owned initiatives that reduce the risks for consumers (Zou et al., 2024) may be more effective for lower-income households and should be implemented alongside existing incentive programs for new EVs. Supporting lower-income households could also include providing incentives to help cover the costs of home charger installation and supporting and developing programs that install chargers in multi-unit housing.

Further, we are able to partition the education and income effects into several attitudinal pathways that reveal how attitudes influence adoption. In particular, higher EV adoption rates for those living in higher-income households and those with more formal education are due in large part to higher CMP and GLP. The importance of cost perceptions for EV adoption decisions (which may improve as EV buyers learn more about cost savings after adoption) points to the need for targeted educational campaigns that emphasize total cost of ownership advantages, especially in regions with lower electricity rates, for households who have not yet adopted an EV. Specifically, given that lower-income individuals seem to be motivated more by the rising cost of gas prices, these campaigns should emphasize the financial benefits of EV charging relative to fueling ICEVs. Similarly, given the substantial influence of GLP, the importance of environmental consciousness to the EV adoption decision should not be overlooked. Concurrently, higher income individuals are more heavily influenced by their level of GLP (as seen by the interactions in Table 4) while lower-income individuals are more motivated by more immediate economic concerns even if they have high levels of GLP. Therefore, information provision strategies should be designed to highlight the immediate environmental benefits of EVs, placing these impacts in the context of specific communities. This is especially so for older individuals, who are much more likely to adopt EVs overall and due specifically to the motivation of concerns of climate change, when they have a higher level of GLP. Providing targeted information in this way may help to improve the perceived benefits of EVs for those who place less emphasis on the broader long-term environmental consequences. However, since not all consumers are motivated by pro-environmental attitudes, at some point developing other forms of messaging to appeal to those who are not interested in the environmental benefits will become increasingly necessary.

5.2 Implications for Vehicle Developers and Marketing

EV developers and manufacturers can use the results of this study to tailor their marketing toward specific population segments. For instance, while focusing marketing on environmental benefits may be effective for high income and highly educated populations, who have higher GLP, focusing on improvements to other features of the technology may be more effective for other groups. Those who consider vehicles primarily to serve a functional purpose, such as women, older adults, and Hispanic individuals, are less likely to adopt BEVs, suggesting a misalignment between current EV offerings and the perceived practical needs of significant market segments. The lack of interest in BEVs among those whose decisions are more functionally driven could also be indicative of the early stage of the EV market, and particularly a lack of confidence in BEVs compared with PHEVs. Developers should prioritize addressing the specific concerns of these individuals, such as enhancing battery performance and range capabilities to alleviate anxieties prevalent among older adults or highlighting the longer-term maintenance benefits for women or Hispanic individuals. Additionally, given that those with higher levels of VFP are more likely to adopt due to the ability to charge at home, emphasizing the benefits of home charging, ensuring that charging processes are simplified and easy to use, and providing mechanisms to familiarize those who are uncomfortable with the technologies to the charging process would be beneficial. Simultaneously, marketers should craft targeted

messaging that emphasizes the real-world functionality of BEVs, moving beyond the longer-term environmental appeals to demonstrate how these vehicles can integrate into the daily lives of potential adopters. Specifically, given that low-income individuals may be more likely to be motivated to buy EVs due to economic factors, like rising gas prices (see the motivating reasons for adoption in Table 4), continuing to improve these qualities of EVs and emphasizing these benefits in messaging may be effective strategies to improve adoption rates for a broader segment of the population. Additionally, in contrast to most other individuals, families with children seem to be slightly more likely to adopt EVs when they consider the role of the vehicle to be practical rather than social. This may be due to the different functional needs of families with children, including prioritization of safety as well as additional space in the interior of the vehicle. Vehicle manufacturers should emphasize these attributes more heavily, particularly when marketing to parents, but also when addressing broader populations who have an interest in vehicle functionality but may be less likely to seek out information about these specific attributes.

Furthermore, the results of the motivating reasons for adoption (see Table 4) demonstrate the important role of practical experience in EV appeal. The significant influence of hands-on experience in mitigating range anxiety and fostering adoption, particularly among high-income individuals and older adults, points to the potential efficacy of experiential marketing techniques. Implementing widespread test drive programs, interactive demonstrations, and community-based EV sharing initiatives could provide the practical exposure necessary to demystify EV technology and address misconceptions across a broader spectrum of potential adopters. By combining pointed messaging with opportunities for direct engagement, the EV industry can create a more inclusive narrative that addresses the diverse concerns and preferences of various consumer segments, potentially spurring a more rapid and widespread transition to electric mobility.

5.3 Implications for Planning and Infrastructure Development

Several results relating to charging station availability as well as perceptions of EV batteries and range have important implications for transportation planning and infrastructure development strategies. We find that about 44% of the total ATE of charging station density on EV adoption is an indirect effect through BRP, while the remaining 56% is through a direct effect. Although the effect of charging density may, in part, reflect that charging providers prioritize development in areas with high adoption rates, this shows that infrastructure alone does not influence EV adoption, and that perceptions of range and charging are an important mediator. This suggests that infrastructure deployment should be approached both as a tool for addressing range anxiety as well as influencing adoption in other ways. Notably, individuals living in areas with high charging station density tend to attribute adoption to having heard about EVs from family members or friends. Similarly, those with higher BRP are more likely to adopt due to the specific motivating reason of having heard about EVs from friends or family members. This indicates that charging infrastructure appears to serve a dual purpose, providing practical benefits by alleviating range concerns while simultaneously functioning as a form of passive marketing that normalizes EV usage within the urban landscape. Therefore, transportation planners should consider both the functional and psychological dimensions of charging infrastructure placement, prioritizing high-visibility locations that can maximize both practical utility and public awareness.

The ATE results also reveal that charging perceptions vary significantly across different populations with a notable disconnect between charging perceptions and actual adoption rates for non-white individuals and those living in multifamily dwellings. Despite having more favorable perceptions of EV capabilities, neither of these groups seem to adopt EVs at higher rates than others. This finding highlights an important gap in current charging infrastructure planning and highlights the need to consider different approaches, particularly in urban areas with high concentrations of apartment complexes and other multifamily units. These residents may have more access to public charging infrastructure but lack cheap and convenient home charging infrastructure more readily available for those living in single-family homes. Transportation planners should consider implementing comprehensive charging solutions that specifically target multi-unit residential developments. Such policies could include requirements for the provision of dedicated charging spaces within apartment complex parking facilities and the development of shared charging facilities in

residential neighborhoods. Additionally, innovative solutions such as removable batteries, battery swaps, and mobile charging services should be explored for those without regular access to electrified parking spaces at their residence. Further, although there is no significant difference in BRP between men and women, the fact that men seem more likely to adopt because of the ability to charge at home is notable and suggests that women may be less convinced by the in-home charging convenience of EVs even as range improves. It may also suggest that women, who have a higher VFP and generally desire more mobility control (see Hjorthol, 2008) may place a higher premium on out-of-home charging to maintain this control. Thus, the improvement of out-of-home charging infrastructure may be a particularly important step to encourage adoption among women.

6. CONCLUSIONS

This research demonstrates that electric vehicle adoption rates are influenced by a wide range of factors, including individual-level demographics, attitudes and lifestyle preferences, perceptions of EVs capabilities, and infrastructure availability. In this paper, we examine this individual-level adoption decision using revealed preference data from California residents. Jointly, we examine the motivations for adoption, revealing the multitude of pathways that lead different individuals to choose EVs. The results highlight the need for a multifaceted approach to promoting EVs that accounts for the different needs of diverse populations. Specifically, while environmental issues play a significant role in adoption decisions for many individuals, we find that vehicle functionality is an area that should be emphasized to better correspond with the interests of women, older individuals, and Hispanic individuals. We also find that income plays a large role in EV adoption decisions, perhaps because of the early stage of the EV market and higher prices for EVs compared to ICEVs, both of which highlight the need for increased incentives. In addition, charging infrastructure seems to play a role in EV adoption both by improving perceptions of EV range performance and through additional social mechanisms that make EV technologies more visible. Further, existing studies have noted a disconnect between the ease of home charging and heightened preferences for EVs among those living in single-family homes in stated preference surveys and higher adoption rates in urban areas with greater proportions of multifamily dwellings in aggregate studies. We explore the factors that lead to adoption for these two groups and find that different factors influence adoption for each group. Our findings confirm a heightened interest in home-charging for those living in single-family homes, while a more positive perception of EV range and battery technology (likely related to access to and knowledge of charging stations) influences those living in multifamily dwellings or apartments.

While this research presents new findings related to the decision to adopt an EV, there are many possible directions for future research. Due to the small sample of PHEV adopters, we were only able to model differences in propensities for BEV and PHEV adoption in a limited way. Future studies could break down choices based on different EV types (BEV versus PHEV) as well as examine how preferences for different vehicle attributes (such as body type or model) relate to the fuel type decision. Additionally, while our study was limited to California, future research may consider whether the decision to adopt an EV is related to similar factors in other US states, including regions with less EV charging infrastructure or fewer incentives. Considering a broader set of geographies and including a more comprehensive representation of local and regional charging infrastructure would provide valuable insights into the continued development of infrastructure at a local, national, and global level. Further, an investigation of how preferences for EVs are impacted by existing and planned travel needs and travel patterns (including commute distance) would be of interest, particularly due to the close connection between these travel patterns and specific needs for battery range and charging capabilities. Finally, as the EV market evolves and the EV secondary market grows, future research could investigate decisions regarding the adoption of used EVs.

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Table 1: Descriptive Statistics of Exogenous Variables

Variable	Sample Count	Sample Percent	ACS Percent	Variable	Sample Count	Sample Percent	ACS Percent
<i>Individual Demographics</i>							
Age				Gender			
18-34	173	15.8	34.5	Male	630	57.4	50.1
35-49	241	21.9	28.7	Female	468	42.6	49.9
50-64	360	32.8	23.4	Employment			
65+	324	29.5	13.4	Employed	648	59.0	73.3
Race				Unemployed	135	12.3	6.2
White	792	72.1	48.1	Retired	315	28.7	20.5
Not White	306	27.9	51.9	Educational Attainment			
Ethnicity				Less than bachelor's degree	383	34.9	56.1
Hispanic	252	23.0	39.7	Bachelor's degree	346	31.5	30.1
Not Hispanic	846	77.0	60.3	Graduate degree	369	33.6	13.8
<i>Household Demographics</i>							
Number of Adults				Presence of Children			
1	197	17.9	23.9	Yes	393	35.8	42.6
2+	901	82.1	76.1	No	705	64.2	57.7
Household Income				Household Type			
0-99,999	490	44.6	53.6	Single-family home	937	85.3	65.2
100,000-199,999	377	34.3	28.5	Multifamily home or apartment	161	14.7	34.8
200,000+	231	21.1	17.9				
<i>Residential Location</i>							
Population Density				Charging Density			
Low	708	64.5	61.6	Low	400	36.4	49.3
High	390	35.5	38.4	Medium	361	32.9	29.0
				High	337	30.7	21.7

Table 2: Distribution of Ranked Reasons for EV Purchase

Reason for buying an EV	Unweighted Shares			Weighted Shares		
	Top rank	Second rank	Third rank	Top rank	Second rank	Third rank
Rising gasoline prices	14.1	11.2	16.5	14.6	9.6	16.2
Take advantage available incentives	8.6	15.5	18.6	9.6	15.5	16.1
Interest in the technology	15.6	14.8	13.0	15.4	13.3	17.0
Interest in specific brand/model of electric vehicle	11.3	9.4	9.5	11.7	10.6	10.1
Test drove one	3.4	5.8	8.1	3.5	7.5	8.3
Heard about EVs from friends/family or colleagues	4.1	6.9	5.2	5.1	6.7	4.6
The ability to charge/"refuel" at home	8.4	20.4	16.8	8.2	20.7	14.5
Concerns about climate change	34.5	16.0	12.3	31.9	16.1	13.2

Table 3: Determinants of Latent Variables

Latent Variable Structural Equation Model	Green Lifestyle Propensity		Vehicle Functionality Preference		EV Cost and Maintenance Perception		EV Battery Range and Charging Perception	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Gender (male)								
Female	0.18	2.89	0.23	2.28	-0.59	-6.03	--	
Age (18-34)								
35-49	--		--		--		-0.42	-3.07
50-64	--		0.27	2.16	--		-0.62	-5.02
65+	--		0.53	3.92	--		-0.66	-5.77
Ethnicity (not Hispanic)								
Hispanic	-0.41	-3.75	0.31	2.26	-0.53	-4.11	0.41	3.47
Race (white)								
Non-white	--		--		--		0.17	2.01
Employment (employed)								
Retired	--		--		0.24	2.37	--	
Education (less than bachelor's degree)								
Bachelor's degree	0.53	4.85	--		0.54	4.39	--	
Graduate degree	0.82	6.70	--		0.73	5.76	0.22	2.07
Household income (less than \$100,000)								
\$100,000 - \$199,999	--		--		0.35	3.16	--	
\$200,000+	0.29	2.23	--		0.57	3.46	--	
Household type (single-family home)								
Multifamily home or apartment	--		--		--		0.28	2.41
Charging station density (low)								
Medium	--		--		--		0.12	1.82
High	--		--		--		0.23	2.71
Latent Variable Measurement Equation Model	Loading	t-stat	Loading	t-stat	Loading	t-stat	Loading	t-stat
I feel a personal obligation to do my part to move the country toward a renewable energy future	1.26	11.23	--		--		--	
I feel a personal obligation to do my part to address climate change	1.44	9.62	--		--		--	
I feel guilty when I waste energy	0.99	16.02	--		--		--	
For me, vehicles have practical purposes only	--		0.91	10.04	--		--	
The functional quality of a vehicle is more important than its make	--		0.89	10.34	--		--	
A vehicle provides status and prestige	--		-0.83	-12.33	--		--	
EVs have a better return on investment	--		--		0.97	15.58	--	
EVs have better maintenance requirements	--		--		1.30	14.60	--	
EVs have a better operating cost	--		--		1.26	15.33	--	
EVs have a better driving range before needing to refuel	--		--		--		1.05	12.37
EVs have better convenience of refueling/charging	--		--		--		0.96	11.28
EVs are good for long-distance trips	--		--		--		1.21	15.21
Correlations between Latent Variables			Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Green Lifestyle Propensity	--		0.17	2.64	0.56	10.07	0.43	7.27
Vehicle Functionality Preference	--		--		0.09	1.57	0.08	1.69
EV Cost and Maintenance Perception	--		--		--		0.54	11.09

Table 4: Main Estimation Results

Variables (base)	EV ownership		Rising gas prices		Take advantage of incentives		Interest in the technology		Interest in a specific brand/model		Test drove one		Heard about EVs from friends/family		Ability to charge at home		Concerns about climate change	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	-1.80	-5.39	--		-3.08	-7.05	-0.47	-2.16	-1.52	-5.16	-1.99	-7.09	-2.26	-5.04	-0.81	-2.70	-1.65	-2.28
<i>Latent Constructs and Interactions</i>																		
GLP	1.14	4.76	--		-0.30	-1.36	--		--		--		--		--		1.83	2.57
GLP * Age 35-49	0.49	2.27	--		--		--		--		--		--		--		0.32	1.32
GLP * Age 50-64	0.64	2.58	--		--		--		--		--		--		--		0.52	1.93
GLP * Age 65+	0.72	2.15	--		--		--		--		--		--		--		0.76	2.55
GLP * Income \$100,000 - \$199,999	0.39	1.44	--		--		--		--		--		--		--		0.59	2.21
GLP * Income \$200,000+	0.61	1.62	--		--		--		--		--		--		--		0.61	2.35
VFP	-0.69	-4.75	--		1.00	2.34	--		-0.45	-1.28	--		--		1.20	3.79	--	
VFP * PHEV	0.73	1.67	--		--		--		--		--		--		--		--	
VFP * Age 35-49	-0.31	-1.72	--		--		--		--		--		--		--		--	
VFP * Age 50-64	-0.50	-3.10	--		--		--		--		--		--		--		--	
VFP * Age 65+	-0.55	-2.15	--		--		--		--		--		--		--		--	
VFP * Income \$100,000 - \$199,999	-0.40	-2.00	--		--		--		--		--		-0.42	-1.39	--		--	
VFP * Income \$200,000+	-0.77	-2.72	--		--		--		--		--		-0.55	-1.80	--		--	
VFP * Presence of children	0.56	3.20	--		--		--		--		--		--		--		--	
CMP	1.31	6.48	0.79	3.72	1.11	3.44	0.42	2.00	--		--		--		0.46	1.86	-0.92	-2.25
CMP * PHEV	0.59	1.75	--		--		--		--		--		--		--		--	
CMP * Income \$100,000 - \$199,999	--		-0.27	-1.35	--		--		--		--		--		--		--	
CMP * Income \$200,000+	--		-0.32	-1.65	--		--		--		--		--		--		--	
CMP * Presence of children	0.46	2.07	--		--		--		--		--		--		--		--	
BRP	0.99	4.19	--		-0.87	-3.35	--		1.31	3.39	0.63	2.43	0.40	1.60	--		-1.31	-3.28
BRP * Multifamily home or apartment	0.53	1.92	--		--		--		--		--		--		--		--	
<i>Individual Demographics</i>																		
Gender (male)																		
Female	--		--		--		-0.36	-2.19	--		--		--		-0.67	-2.86	--	
Age (18-34)																		
35-49	--		--		1.15	3.74	--		--		--		--		--		--	
50-64	--		--		1.15	3.74	--		0.30	1.32	0.42	1.74	--		--		--	
65+	--		--		1.32	3.65	--		0.64	1.80	0.42	1.74	--		--		--	
Ethnicity (not Hispanic)																		
Hispanic	-0.38	-2.14	--		--		--		--		--		--		--		--	
Race (white)																		
Non-white	-0.29	-1.99	--		--		--		--		--		--		--		--	

Table 4: Main Estimation Results (cont.)

Variables (base)	EV ownership		Rising gas prices		Take advantage of incentives		Interest in the technology		Interest in a specific brand/model		Test drove one		Heard about EVs from friends/family		Ability to charge at home		Concerns about climate change	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	-1.80	-5.39	--		-3.08	-7.05	-0.47	-2.16	-1.52	-5.16	-1.99	-7.09	-2.26	-5.04	-0.81	-2.70	-1.65	-2.28
Education (less than bachelor's degree)																		
Bachelor's degree	0.52	2.14	--		--		--		--		--		--		--		--	
Graduate degree	1.01	3.90	--		--		--		--		--		--		--		--	
<i>Household Demographics and Location</i>																		
Household composition (2+ adults)																		
Single adult	-0.46	-2.10	--		-0.48	-1.72	--		--		--		0.77	3.09	0.48	1.63	--	
Presence of children * PHEV	1.21	3.29	--		--		--		--		--		--		--		--	
Household income (less than \$100,000)																		
\$100,000 - \$199,999	0.37	1.74	-0.79	-3.12	--		--		0.65	2.54	0.78	2.76	0.34	1.45	--		--	
\$200,000+	1.11	3.79	-0.79	-3.12	--		--		0.84	3.20	1.07	3.71	0.93	3.45	--		--	
Household type (single family home)																		
Multifamily home or apartment	-0.46	-2.32	--		1.08	3.24	--		--		--		--		-0.38	-1.47	--	
Multifamily home or apartment * PHEV	0.50	1.68	--		--		--		--		--		--		--		--	
Population density (low)																		
High	0.29	1.78	0.21	1.47	0.68	3.31	--		--		--		--		-0.25	-1.31	0.73	2.77
Charging station density (low)																		
Medium	0.28	1.85	--		--		--		--		--		0.44	2.15	--		--	
High	0.31	2.23	--		--		--		--		--		0.58	3.29	-0.23	-1.41	--	

Table 5: Model Fit

Disaggregate Fit Measures										
Metric			Proposed GHDM		GHDM without Correlations		IHDM			
Log-Likelihood at Convergence			-20216.75		-20371.97		--			
Log-Likelihood at Constants			-22977.05		-22977.05		--			
Bayesian Information Criterion			20871.37		21005.58		--			
Adjusted Likelihood Ratio Index			0.114		0.108		--			
Likelihood Ratio Test between Proposed GHDM and GHDM without Correlations					310.43					
Predictive Log-Likelihood at Convergence			-2300.77		-2322.80		-2753.56			
Predictive Log-Likelihood at Constants			-2964.28		-2964.28		-2964.28			
Number of Non-Constant Parameters			131		125		105			
Predictive Bayesian Information Criterion			2955.38		2956.41		3149.13			
Predictive Adjusted Likelihood Ratio Index			0.180		0.174		0.036			
Informal Predictive Likelihood Ratio Test between Proposed GHDM and GHDM without Correlations					44.06					
Informal Predictive Non-Nested Likelihood Ratio Test between Proposed GHDM and IHDM					-29.66					
Average Probability of a Correct Prediction			0.428		0.392		0.378			
Aggregate Fit Measures										
Outcome Combinations			Observed (Weighted)		Proposed GHDM		GHDM without Correlations		IHDM	
EV Adoption	First Ranked Reason		Shares		Share	APE	Share	APE	Share	APE
No	--		94.83		94.82	0.01	93.52	1.38	93.21	1.71
Yes	Rising gasoline prices		0.75		0.99	30.74	0.87	14.61	1.12	48.59
	Take advantage available incentives		0.50		0.60	20.25	0.62	24.06	0.55	9.85
	Interest in the technology		0.80		0.83	4.94	0.41	49.10	0.44	44.28
	Interest in specific brand/model of electric vehicle		0.61		0.52	14.72	1.18	95.88	1.26	108.70
	Test drove one		0.18		0.16	12.24	0.11	37.66	0.13	27.86
	Heard about EVs from friends/family or colleagues		0.26		0.20	23.55	0.10	61.86	0.10	60.58
	The ability to charge/"refuel" at home		0.42		0.90	111.29	0.57	34.91	0.89	110.12
	Concerns about climate change		1.65		0.98	40.37	2.62	58.91	2.30	39.18
Weighted Average Percent Error (WAPE)					1.69		3.86		4.37	

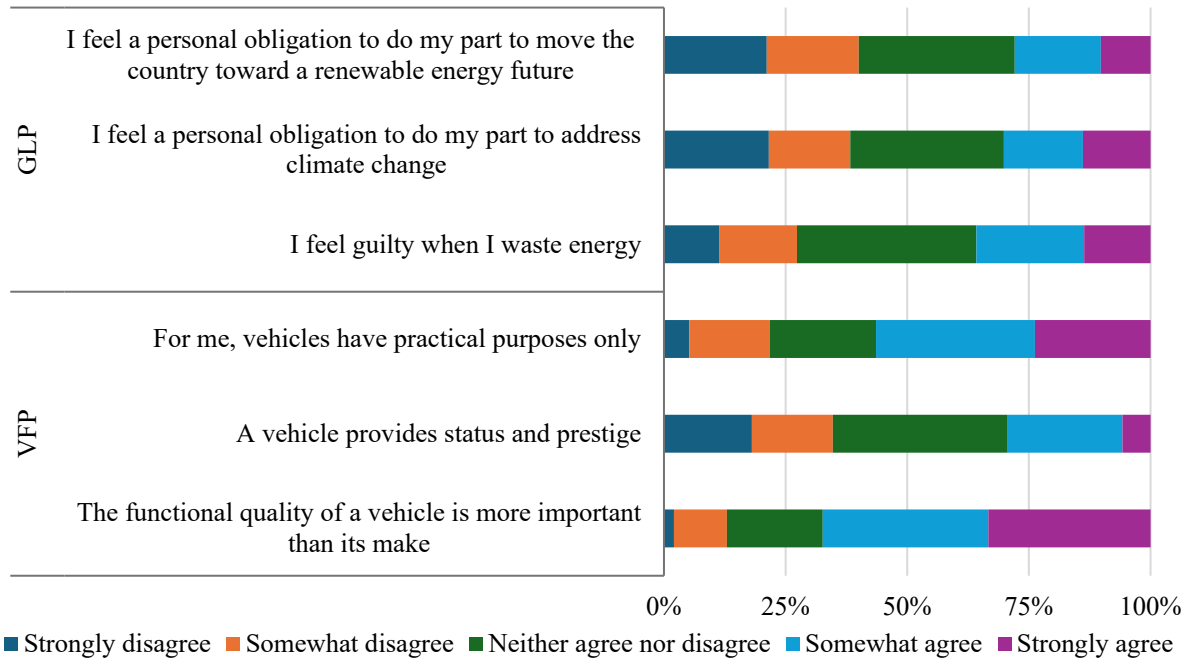
Table 6: Measures of Fit by Market Segment of the Estimation Sample

Measures of Fit	Proposed GHDM	GHDM without Correlations	IHDM	Measures of Fit	Proposed GHDM	GHDM without Correlations	IHDM
Market Segment	Age: 55-64			Market Segment	Gender: Male		
Number of Observations		360		Number of Observations		630	
Predictive Log-Likelihood	-702.18	-709.36	-843.35	Predictive Log-Likelihood	-1304.14	-1317.96	-1541.52
Informal Predictive LRT		14.35		Informal Predictive LRT		27.66	
Informal Predictive non-Nested LRT			-15.95	Informal Predictive non-Nested LRT			-21.18
WAPE	2.14	3.78	4.26	WAPE	3.01	5.49	5.65
Market Segment	Race: White			Market Segment	Employment: Employed		
Number of Observations		792		Number of Observations		648	
Predictive Log-Likelihood	-1616.51	-1623.09	-1921.91	Predictive Log-Likelihood	-1440.58	-1457.68	-1674.43
Informal Predictive LRT		13.16		Informal Predictive LRT		34.22	
Informal Predictive non-Nested LRT			-24.18	Informal Predictive non-Nested LRT			-21.02
WAPE	1.57	3.72	4.25	WAPE	2.63	6.05	6.15
Market Segment	Ethnicity: Not Hispanic			Market Segment	Education: Less than Bachelor's		
Number of Observations		846		Number of Observations		383	
Predictive Log-Likelihood	-1726.80	-1739.60	-2079.77	Predictive Log-Likelihood	-535.69	-542.26	-612.92
Informal Predictive LRT		25.60		Informal Predictive LRT		13.15	
Informal Predictive non-Nested LRT			-26.08	Informal Predictive non-Nested LRT			-10.74
WAPE	2.47	5.45	5.72	WAPE	3.61	4.58	5.10
Market Segment	Number of Adults: 2+			Market Segment	Presence of Children: No		
Number of Observations		901		Number of Observations		705	
Predictive Log-Likelihood	-1839.62	-1849.58	-2207.69	Predictive Log-Likelihood	-1377.85	-1385.36	-1661.72
Informal Predictive LRT		19.93		Informal Predictive LRT		15.03	
Informal Predictive non-Nested LRT			-26.65	Informal Predictive non-Nested LRT			-23.28
WAPE	2.23	4.18	4.64	WAPE	2.14	2.88	3.55
Market Segment	Household Income: < \$100,000			Market Segment	Housing Type: Single-Family		
Number of Observations		490		Number of Observations		937	
Predictive Log-Likelihood	-918.05	-935.95	-1031.49	Predictive Log-Likelihood	-1898.96	-1907.02	-2266.91
Informal Predictive LRT		35.81		Informal Predictive LRT		16.11	
Informal Predictive non-Nested LRT			-12.85	Informal Predictive non-Nested LRT			-26.64
WAPE	2.69	2.77	3.39	WAPE	1.82	4.05	4.62
Market Segment	Population Density: Low			Market Segment	Charging Density: Low		
Number of Observations		708		Number of Observations		400	
Predictive Log-Likelihood	-1401.62	-1410.54	-1681.94	Predictive Log-Likelihood	-715.94	-722.58	-868.30
Informal Predictive LRT		17.82		Informal Predictive LRT		13.28	
Informal Predictive non-Nested LRT			-23.12	Informal Predictive non-Nested LRT			-16.48
WAPE	2.01	2.82	3.60	WAPE	1.78	2.60	2.63

Table 7: Average Treatment Effects

Variable	Base Level	Treatment Level	Percent Contribution Through				Percent Direct Effect	Total ATE
			GLP	VFP	CMP	BRP		
Gender	Male	Female	22	-17	-61	0	0	-0.0668
Age	18-34	65+	24	-39	0	-37	0	-0.0849
Ethnicity	Not Hispanic	Hispanic	-28	-12	-30	16	-14	-0.1490
Race	White	Non-white	0	0	0	39	-61	-0.0083
Employment	Employed	Retired	0	0	100	0	0	0.0293
Education	Less than bachelor's degree	Graduate degree	40	0	28	6	26	0.3379
Number of Adults	Two or more	Single adult	0	0	0	0	-100	-0.0364
Presence of Children	No	Yes	0	38	38	0	24	0.0467
Income	Less than \$100,000	\$200,000 or more	29	-8	27	0	36	0.2281
Housing Type	Single family home	Multifamily home or apartment	0	0	0	48	-52	-0.0012
Population Density	Low	High	0	0	0	0	100	0.0208
Charging Density	Low	High	0	0	0	44	56	0.0452

To what extent do you agree or disagree with the following?



Thinking about battery electric vehicles compared to gasoline-powered vehicles, how would you rate battery electric vehicles on each of the following?

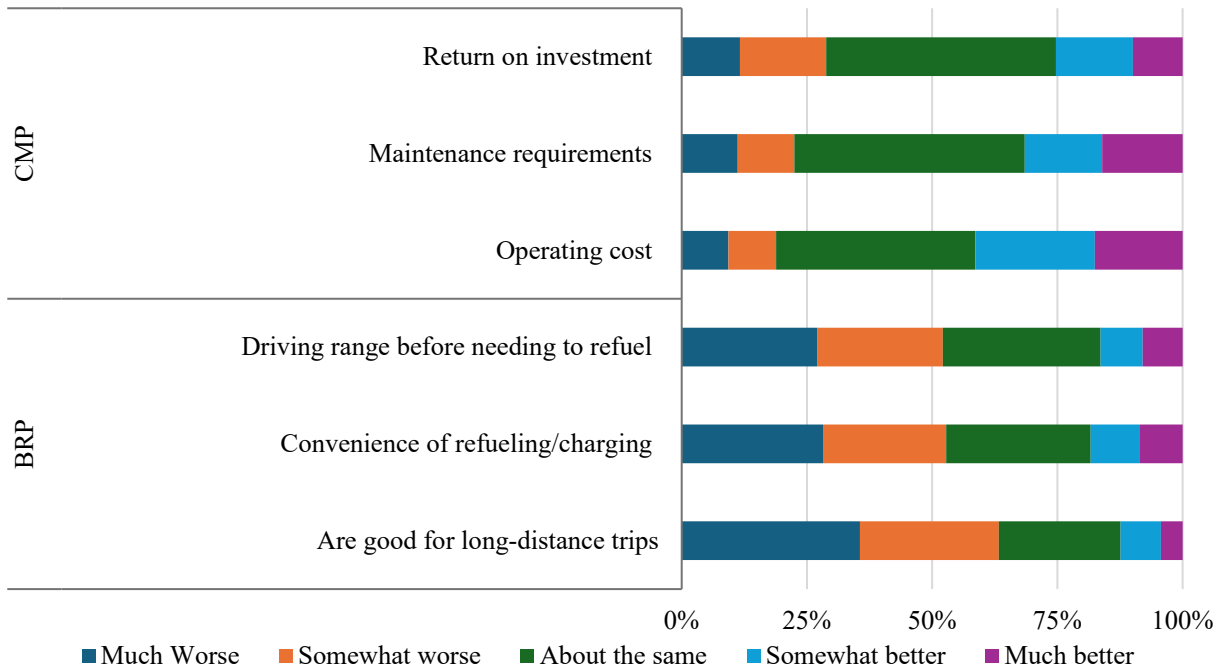


Figure 1: Distribution of Indicators of Latent Constructs

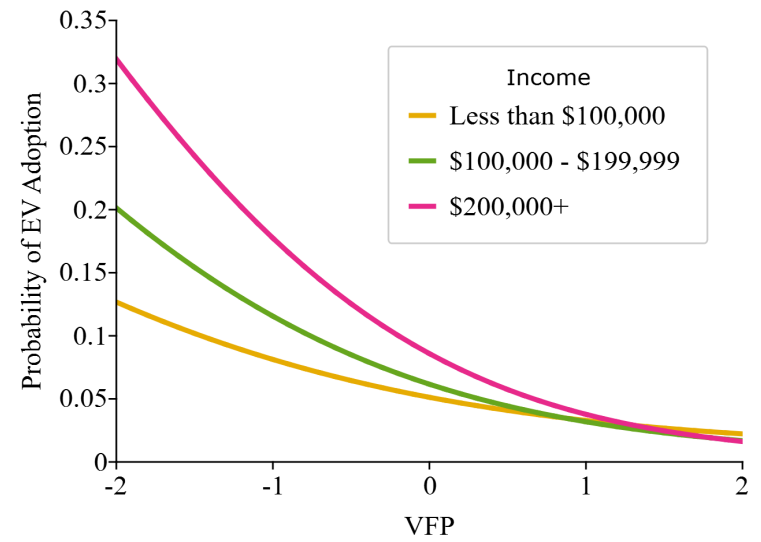
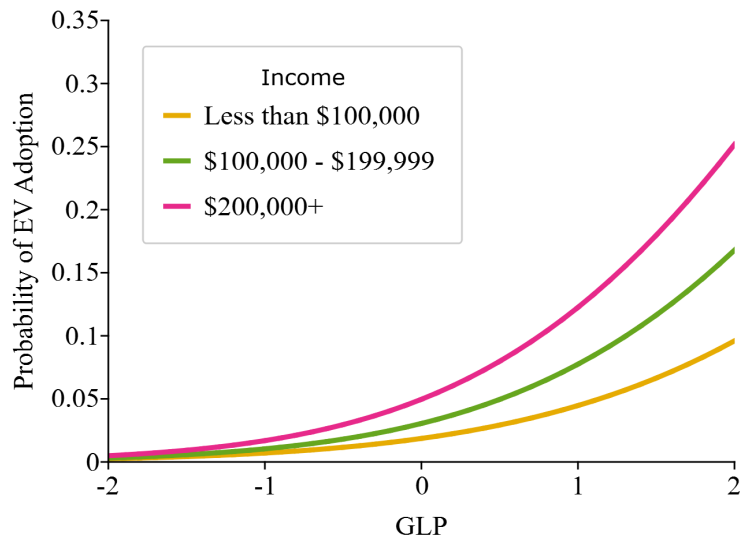
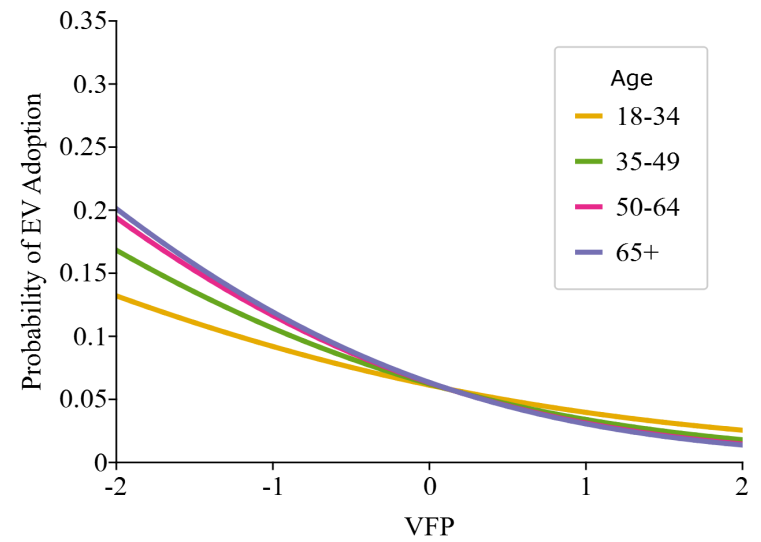
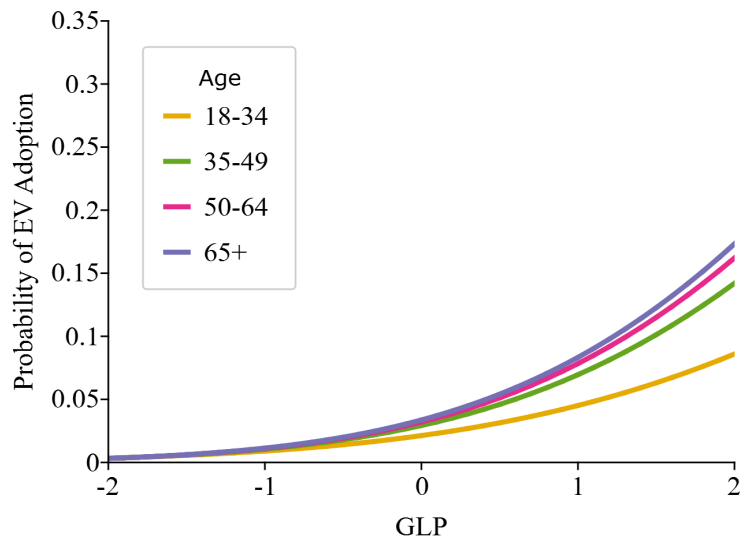


Figure 3: Interaction Effects of Age and Income with GLP and VFP on Probability of EV Adoption