Project Report

# Latent Vehicle Type Propensity Segments: Considering the Influence of Household Vehicle Fleet Structure

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

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**16. Abstract**

This study applies latent class cluster analysis to a sample of 1,111 survey respondents in Georgia, identifying naturally occurring vehicle type segments based on the influence of both individual vehicle type choices and household vehicle fleet structures. The developed model identifies seven latent vehicle type propensity segments, six of which include individuals who reported being the main driver for (respectively) car, SUV/van, and truck. In three of those segments this was generally their only available vehicle, while in the other three the "main driver" vehicle accompanied other available household vehicles. The seventh segment captures individuals who are main drivers of multiple vehicle types, and who also have other household vehicles available for use. We generate user profiles and discuss differences across segments regarding individual-level characteristics (e.g., gender), household-level characteristics (e.g., household income), land-use and travel-related preferences (e.g., neighborhood type, share of household-serving trips), attitudes (e.g., materialistic), and targeted marketing data variables (e.g., support for charitable causes). Selected results suggest that women choose SUVs/vans due to both personal preferences (e.g., feeling safer while driving a large vehicle) and household responsibilities; show that vehicle-owning behaviors and attitudes are generally consistent, except that strong pro-vehicle-owning attitudes exist within vehicle-deficit households; and suggest that vehicle-deficit households may be less open to alternative fuel vehicles, possibly due to reliability concerns. Overall, this study provides a new perspective on vehicle type propensity segments, and examines the association of a novel range of general and travel-related attributes with these segments, yielding nuanced insights with potential policy implications.

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**EXECUTIVE SUMMARY**
This study applies latent class cluster analysis to a sample of 1,111 survey respondents in Georgia, identifying naturally occurring vehicle type segments based on the influence of both individual vehicle type choices and household vehicle fleet structures. The developed model identifies seven latent vehicle type propensity segments, six of which include individuals who reported being the main driver for (respectively) car, SUV/van, and truck. In three of those segments this was generally their only available vehicle, while in the other three the "main driver" vehicle accompanied other available household vehicles. The seventh segment captures individuals who are main drivers of multiple vehicle types, and who also have other household vehicles available for use. We generate user profiles and discuss differences across segments regarding individual-level characteristics (e.g., gender), household-level characteristics (e.g., household income), land-use and travel-related preferences (e.g., neighborhood type, share of household-serving trips), attitudes (e.g., materialistic), and targeted marketing data variables (e.g., support for charitable causes). Selected results suggest that women choose SUVs/vans due to *both* personal preferences (e.g., feeling safer while driving a large vehicle) *and* household responsibilities; show that vehicle-owning behaviors and attitudes are generally consistent, except that strong pro-vehicle-owning attitudes exist within vehicle-deficit households; and suggest that vehicle-deficit households may be less open to alternative fuel vehicles, possibly due to reliability concerns. Overall, this study provides a new perspective on vehicle type propensity segments, and examines the association of a novel range of general and travel-related attributes with these segments, yielding nuanced insights with potential policy implications.

## 1. INTRODUCTION

Understanding vehicle type propensities and choices is of interest to academics and practitioners in a wide array of fields. For example, market researchers may study vehicle type choices to predict consumer purchase behaviors and future market shares (Train and Winston, 2007), while energy researchers study individuals' vehicle type preferences and corresponding driving habits to calculate energy consumption and emissions (Gao et al., 2019). Transportation scholars traditionally study vehicle type to understand and forecast individual and household travel behaviors (Bhat and Sen, 2006), while in recent times, there has been a proliferation of vehicle type studies intended to model the adoption of emerging transport technologies such as electric and automated vehicles (Higgins et al., 2017; Mocanu, 2018). In this study, we investigate vehicle type from a travel behavior perspective, identifying segments with the aim of understanding how personal and household mobility needs, along with a novel range of individual- and household-level characteristics, attitudes, and behaviors, influence vehicle type propensities. Based on the developed model, we further examine the relationships between vehicle type propensities, gender roles, attitudes, and current and future travel behavior choices/interests, focus areas that can have policy implications in transportation.

A substantial body of literature has classified *vehicle type*, using a variety of deterministic schemes. Examples of individual attributes used for vehicle type classification include vehicle size (Lave and Train, 1979), body type (Cao et al., 2006), fuel type (Hoen and Koetse, 2014), and make/model (Østli et al., 2017). Other studies have combined attributes and developed mixed classification schemes (Baltas and Saridakis, 2013). Typically, *individuals* are then deterministically classified on the basis of the type of the vehicle they drive most often.

The present paper focuses on classifying people, based on the types of vehicles for which they are the main driver, but it (1) also takes into account the entire household fleet of vehicles; (2) draws on a wide range of covariates to portray the kinds of people in each segment; and (3) uses a probabilistic clustering approach, latent class cluster analysis (LCCA). LCCA offers some potential advantages over deterministic approaches. For one thing, statistical criteria to aid in identifying an optimal number of clusters are built into the method (Vermunt and Magidson, 2002). Further, due to the structure of the model, the resultant latent clusters may be more homogeneous than deterministic classifications. For all of the above reasons, we believe that the LCCA model developed in this study could provide new insights into vehicle type propensity segments in the population.

The rest of this report is organized as follows. We begin with a review of the literature on vehicle type classification, focusing especially on user profiles and modeling methods (Section 2). We introduce the data sources used in the present study in Section 3, and present the modeling framework in Section 4. In Section 5, we detail the latent vehicle type propensity segments identified by the LCCA model and generate and discuss resultant segment profiles. In Section 6, we further interpret the model, seeking to shed new light on how vehicle type propensities are influenced by traditional gender roles, as well as to examine how vehicle type propensities relate to attitudes and current and future travel behavior choices/interests. We close with a summary of findings (Section 7).

## 2. LITERATURE REVIEW

Vehicle ownership is a key behavioral indicator, of which *vehicle type choice* is an important subarea of interest due to its important role in an array of fields, ranging from consumer forecasting to energy consumption, emission modeling, and travel behavior analysis, among others. Previous

studies have shown that users choosing the same vehicle type have a discernible tendency to share similar characteristics (e.g., age, gender, income). In transportation, generating and understanding vehicle type user profiles can provide key insights for transport supply and demand modeling, as well as urban planning and policy making processes. In this section, we first review and summarize existing findings on user characteristics associated with common vehicle types (Section 2.1). We then provide an overview of the classic methods used for vehicle type modeling and user profiling (Section 2.2).

### 2.1 Typical Vehicle Type User Profiles: A Summary from Previous Studies

Most studies classify vehicle users based on the vehicle types that they drive. Therefore, the classification scheme of vehicle types directly influences the corresponding user profiles. In previous studies, vehicle type classification schemes are usually developed based on criteria such as vehicle size, body type, fuel type, price, make/model, vintage level, etc. Some studies also form vehicle classification schemes by combining multiple criteria. For example, Mohammadian and Miller (2003) first classified vehicles into six categories mainly based on the vehicle size, and further classified each vehicle type into four vintage levels (i.e., brand new, secondhand, used, and old). Bhat et al. (2009) defined 20 vehicle types based on the combination of vehicle body types and vintage levels. Baltas and Saridakis (2013) first grouped vehicles by vehicle size, and then identified vehicle types by special categories (e.g., roadsters, sport utility vehicles [SUVs], etc.) to form a 12-category vehicle classification scheme. As shown, vehicle classification schemes vary across studies due to different research objectives and/or dataset restrictions. To enable comparison across studies, we will primarily examine user characteristics of three common vehicle types, i.e., car, SUV/van, and truck.

Existing literature has examined the influence of a wide range of factors on vehicle type choices, with the most common factors studied including vehicle characteristics (e.g., fuel economy, performance, safety, and styling), sociodemographic characteristics, built environment attributes, and individual attitudes. The role of vehicle characteristics in influencing vehicle type choices is relevant primarily in marketing studies (e.g., to analyze customers' willingness to purchase a new vehicle model); and thus, here we do not further discuss the role of vehicle attributes, but instead simply provide selected references on that subject for interested readers (Liu et al., 2014, Greene et al., 2018). On the other hand, the literature has repeatedly shown sociodemographic characteristics and built environment attributes to be essential in modeling travel behavior, including vehicle type choices (Cao et al., 2006, Eluru et al., 2010, Potoglou, 2008). Resultingly, in **TABLE 1**, we summarize findings from the literature on the sociodemographic and built environment characteristics found to be associated with users of the three most common vehicle types (i.e., car, SUV/van, and truck).

As shown in **TABLE 1**, results from the literature are generally consistent aside from minor discrepancies, the latter of which might be a result of different research contexts and/or differing vehicle classification schemes. In terms of overall tendencies (rather than absolute distinctions), car and SUV/van drivers are seen to be younger than truck drivers. Females are seen to prefer driving small cars and SUVs/vans more than males do, while males prefer driving trucks more than females do. Car and SUV/van drivers tend to have higher education levels than truck drivers do. Mid-sized car and minivan/van drivers tend to include a higher proportion of homemakers than average. Household income varies along with vehicle size within the car segment. Generally, household income increases as the car size increases. Studies have also shown that SUV/van drivers are associated with high household incomes while pickup truck drivers are more likely to

have medium incomes. In general, larger households with children are more likely to use spacious vehicles such as mid-sized to large cars and SUVs/vans, whereas households with young children are also likely to use compact cars. Car drivers are more likely to live in urban areas, while truck drivers are more likely to live in low-density areas.

Besides external attributes such as sociodemographic and built environment characteristics, researchers have recognized the important role that personality and attitudes play in vehicle type choice. Choo and Mokhtarian (2004) found that individuals who have pro-high density attitudes (i.e., who prefer living in urban neighborhoods) are more likely to drive smaller cars (small, compact, and mid-sized cars), luxury cars, and SUVs. Along similar lines, Cao et al. (2006) found that individuals with pro-transit attitudes are less likely to choose pickup trucks. People who consider motor vehicles as safer than other modes are more likely to drive SUVs. More recently, researchers have also examined the effects of attitudes on the adoption of alternative fuel vehicles, with several studies finding that environmental concerns and personal/social norms are highly related to electric vehicle (EV) adoption (Mohamed et al., 2016, Smith et al., 2017, White and Sintov, 2017). Orlov and Kallbekken (2019) have also seen that individuals with stronger willingness to try new technologies for the purpose of reducing energy consumption are more likely to own EVs.

**Table 1. Summary of sociodemographic and built environment characteristics associated with common vehicle types**

| | Car | SUV/van | Truck |
|---|---|---|---|
| **Age** | • Choo and Mokhtarian (2004)<br>- Small car drivers have higher than average proportions of people aged 40 or younger. They are more likely to be in the younger age group compared to pickup truck drivers.<br>• Spissu et al. (2009)<br>- The younger age group (16-35 years) is more likely to acquire compact sedans relative to other vehicle types. | • Choo and Mokhtarian (2004)<br>- SUV drivers are more likely to be age 40 or younger.<br>- Minivan/van drivers are more likely to be in the 41-64 age group.<br>• Spissu et al. (2009)<br>- Individuals in the middle-aged group (36–55 years) are more likely to acquire vans relative to other vehicle types. | • Choo and Mokhtarian (2004)<br>- Pickup drivers are more likely to be in the 41-64 age group. |
| **Gender** | • Choo and Mokhtarian (2004)<br>- Small car drivers include higher than average proportions of females.<br>- Small and mid-sized car drivers are more likely to be female compared to pickup truck drivers.<br>• Spissu et al. (2009)<br>- Males are more likely than females to acquire large sedans. | • Choo and Mokhtarian (2004)<br>- SUV and minivan/van drivers are more likely to be female compared to pickup drivers.<br>• Spissu et al. (2009)<br>- Males are more likely than females to acquire SUVs and least likely to acquire vans. | • Choo and Mokhtarian (2004)<br>- Pickup truck drivers are more likely to be male.<br>• Spissu et al. (2009)<br>- Males are more likely than females to acquire pickup trucks. |
| **Education** | • Choo and Mokhtarian (2004)<br>- Drivers of small and mid-sized cars tend to have higher education compared to pickup truck drivers.<br>• Vyas et al. (2012)<br>- Households with a bachelor's degree (as the highest degree across all household members) are less likely than others to own subcompact and large cars.<br>• Baltas and Saridakis (2013)<br>- Small family car drivers have completed higher education levels. | • Choo and Mokhtarian (2004)<br>- SUV and minivan/van drivers are more likely to have higher education compared to pickup drivers.<br>• Vyas et al. (2012)<br>- Households with a bachelor's degree (as the highest degree across all household members) are less likely than others to own large SUVs. | • Choo and Mokhtarian (2004)<br>- Pickup drivers are overrepresented among lower education levels.<br>• Vyas et al. (2012)<br>- Households having individuals with postgraduate degrees are particularly unlikely to prefer pickup trucks. |
| **Race** | • Spissu et al. (2009)<br>- Hispanics are less likely to acquire large sedans than compact sedans.<br>- Asians are more prone to acquiring sedans.<br>• Vyas et al. (2012)<br>- African-Americans are more likely than others to own large cars. | • Spissu et al. (2009)<br>- African-Americans are less likely to acquire vans;<br>- Asians are more prone to acquiring vans.<br>• Vyas et al. (2012) | • Spissu et al. (2009)<br>- African-Americans are less likely to acquire pick-up trucks. |

| | | | |
|---|---|---|---|
| | - Caucasian households are disinclined to own compact cars. | - Caucasian households are disinclined to own large SUVs. | |
| **Employment** | • Choo and Mokhtarian (2004)<br>- Mid-sized car drivers are more likely than average to be homemakers and are less likely to be employed compared to pickup drivers. | • Choo and Mokhtarian (2004)<br>- Minivan/van drivers are more likely to be homemakers and are less likely to be employed compared to pickup drivers. | • Choo and Mokhtarian (2004)<br>- Pickup drivers: overrepresented among full-time employees. |
| **Income** | • Choo and Mokhtarian (2004)<br>- Small car drivers tend to have lower individual incomes compared to pickup drivers.<br>- Mid-sized car drivers tend to have higher household incomes compared to pickup drivers.<br>• Spissu et al. (2009)<br>- Households with high income appear to be more likely to acquire large sedans than compact sedans.<br>• Baltas and Saridakis (2013)<br>- Small family car and mid-sized car drivers are tend to have lower incomes compared to SUV drivers. | • Choo and Mokhtarian (2004)<br>- SUV drivers tend to have higher household incomes compared to pickup drivers.<br>- Minivan/van drivers tend to have higher household incomes and lower personal incomes.<br>• Spissu et al. (2009)<br>- Households with high income appear to be more likely to acquire SUVs and vans compared to compact sedans. | • Choo and Mokhtarian (2004)<br>- Pickup drivers are overrepresented among middle incomes.<br>• Spissu et al. (2009)<br>- Households with high income appear to be less likely to acquire pickup trucks. |
| **Household lifecycle** | • Choo and Mokhtarian (2004)<br>- Mid-sized car drivers tend to have more children (<19 yrs old) in the household compared to pickup drivers.<br>• Bhat et al. (2009)<br>- Households with very young children (<=4 yrs old) are more likely to use compact and midsized sedans than other households.<br>• Spissu et al. (2009)<br>- The presence of children is generally associated with a propensity to acquire large sedans rather than compact sedans.<br>• Vyas et al. (2012)<br>- Households with many adults have the highest preference for compact and large cars. | • Choo and Mokhtarian (2004)<br>- A high proportion of SUV and minivan/van drivers are from larger households with children.<br>• Bhat et al. (2009)<br>- Households with very young children (<=4 yrs old) are more likely to use SUVs than other households.<br>- Households with children prefer minivans.<br>• Spissu et al. (2009)<br>- The presence of children is generally associated with a propensity to acquire SUVs and vans rather than compact sedans.<br>- Larger household sizes are associated with the purchase of vans.<br>• Vyas et al. (2012) | • Vyas et al. (2012)<br>- Households with senior adults are less likely to own pickup trucks. |

| | | | |
|---|---|---|---|
| | | - Households with many adults have the least preference for small SUVs and the highest preference for vans. | |
| **Built environment** | • Choo and Mokhtarian (2004)<br>- Drivers of small cars are more likely to live in urban areas compared to pickup truck drivers. | • Cao et al. (2006)<br>- SUVs fit both urban and suburban cultures. | • Cao et al. (2006)<br>- Individuals living in areas with more space are more likely than others to drive pickup trucks.<br>• Spissu et al. (2009)<br>- Households residing in high employment density areas were less likely than others to acquire pickup trucks. |

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## 2.2 Modeling and Profiling Methods: From Deterministic to Probabilistic

In Section 2.1, we summarized and compared user profiles associated with the primary vehicle types. These user profiles are mainly generated in two ways. The most straightforward approach is to calculate descriptive statistics across user characteristics for each vehicle type and then conduct statistical tests such as analysis of variance (ANOVA) and chi-squared tests to identify significant differences between vehicle type choices (Choo and Mokhtarian, 2004). Since this method is convenient and intuitive, it is usually used by researchers to pre-screen variables of interest for further analysis.

Another widely adopted way to generate user profiles is to first model vehicle type choices and then to generate user profiles based on model coefficients. For example, a positive coefficient for income in the utility function for luxury vehicles indicates an association of higher-income individuals with luxury vehicle ownership. Due to the discrete nature of vehicle types, multinomial logit (MNL) models are most frequently used (Baltas and Saridakis, 2013, Choo and Mokhtarian, 2004). Starting from MNL, other studies refine the model structure to fulfill specific research objectives. For example, Higgins et al. (2017) first segmented vehicles by different types and then constructed MNL models for each vehicle type to model consumer preferences for different types of electric vehicles. Bhat et al. (2009) constructed a nested model structure including a multiple discrete-continuous extreme value (MDCEV) component to analyze vehicle vintage level and vehicle model/make in two nest levels. Hess et al. (2012) carried out a cross-nested logit model to jointly analyze vehicle type choices and fuel type choices. Spissu et al. (2009) studied vehicle type choice and miles of travel simultaneously by constructing a joint discrete-continuous model system.

These vehicle type choice approaches reveal useful and intriguing user profiles of different vehicle types. However, there are two limitations associated with these approaches. First, these studies usually use the most frequently driven vehicle as the sole indicator of the respondent's vehicle type choice. Thus, the models typically do not incorporate information regarding other vehicles that the respondents may also drive. We note that some studies consider the *number* of household vehicles in their model to very simply characterize the household vehicle fleet (Mohammadian and Miller, 2003; Liu et al., 2014). Other studies analyzed vehicle type composition at the *household* level. For example, Bhat and Sen (2006) jointly modeled household vehicle types and their annual miles of use by applying a mixed MDCEV model. Specifically, the study concludes that households are more likely to own passenger cars than other vehicle types, but they may use non-passenger car vehicles more than passenger cars when both vehicle types are available. The study revealed intriguing underlying household preferences for different vehicle types but lacks an individual-level analysis within the household. Second, these approaches first classify vehicle types and then deterministically assign users to different vehicle type groups. While this approach is certainly reasonable, there is also value in a more flexible, probabilistic assignment to groups based on an unobserved propensity to drive a certain type of vehicle. The latter approach may identify people who do not currently drive a certain vehicle type due to various constraints, but who are similar to those who do, and who might easily be persuaded to do so with inducements or constraint mitigations.

To improve upon these limitations, in this study, we (1) consider all vehicles for which the respondent reported being the main driver, as well as the other vehicles present within the household, and (2) probabilistically classify respondents to generate corresponding user profiles, which can improve the homogeneity within vehicle user segments. The method used is latent class cluster analysis (LCCA), which will be discussed in Section 4. We are aware of very few other studies applying latent segmentation approaches to vehicle-type-related studies. Sobhani et al.

(2013) applied a latent segmentation based MDCEV model to analyze trip decisions, which includes vehicle type choices, activity type choices, and accompaniment type choices. Khan et al. (2017) applied a latent class model to study alternative fuel vehicle type choices. Angueira et al. (2019) analyze the interrelationship between vehicle type choice and distance traveled through an LCM. With LCCA, we take a different perspective in the present study – we focus on profiling different vehicle type users with a unique data source including many relevant variables (e.g., attitudes). Our LCCA model also allows us to simultaneously include individual vehicle type choice and household vehicle fleet structure, which provides a new way of examining the influence of household vehicle fleet structure on individual vehicle type choice.

## 3. DATA DESCRIPTION

The dataset used in this study is a novel compilation of multiple data sources. Specifically, the study sample comprises Georgia residents who responded to both the 2017 National Household Travel Survey (NHTS) and the Georgia Department of Transportation Emerging Technologies Survey (GDOT survey). The NHTS is a nationwide travel survey (2017 National Household Travel Survey, U.S. Department of Transportation, Federal Highway Administration), with rich behavioral data that includes a travel diary capturing respondents' activity patterns during a randomly selected day (including both weekdays and weekends across the whole sample). The GDOT survey is a statewide survey conducted on behalf of the Georgia Department of Transportation in 2017-18 (Kim et al., 2019), and is attitudinally-rich with an emphasis on the impacts of emerging technologies on travel behavior in Georgia. In addition to the survey data sources, we have augmented each individual record in the dataset with targeted marketing data (TMD) purchased from a commercial data compiler, as well as with land use variables derived from respondents' residential locations. TMD includes variables such as sociodemographic characteristics, consumer behaviors and propensities, financial information, technology usage, and transport-related attributes (Shaw et al., 2020). **TABLE 2** provides the definition of variables derived from the three data sources for modeling. For the convenience of comparison with segment-specific statistics (i.e., shares/means), descriptive statistics of the overall sample are presented later, in **TABLE 5**.

After data processing and cleaning, the working sample includes 1,111 adults (all from different households) who are recorded as being the main driver for at least one vehicle in the household. We developed case weights for this sample, based on selected demographics obtained from the Census, i.e., sex, age, race, education, work status, Metropolitan Planning Organization (MPO) tier, household income, household size, and vehicle ownership. We modified the process described in Kim et al. (2020) to exclude households ineligible for this study[1]. We applied case weights in both the model calibration and profile development processes to obtain results more representative of the population of Georgia drivers.

[1] From the original working sample of 1,245 adults, we removed 32 zero-vehicle households, 7 non-drivers, 28 individuals either who are not a main driver of any vehicles in the household or for whom the vehicle type that they drive is unknown; 60 people who made no trips on the travel day, and 7 people who could not be matched to TM data.

**Table 2. Variable definitions**

| Category | Variable | Definition |
|---|---|---|
| Indicators | **Main: car** | Indicates whether the respondent was reported as being the main driver of a household vehicle in the car category. |
| | **Main: SUV/van** | Indicates whether the respondent was reported as being the main driver of a household vehicle in the SUV/van category. |
| | **Main: truck** | Indicates whether the respondent was reported as being the main driver of a household vehicle in the truck category. |
| | **Other: car** | Indicates whether there are other available cars (besides those for which the individual is the main driver) in the household. |
| | **Other: SUV/van** | Indicates whether there are other available SUVs/vans (besides those for which the individual is the main driver) in the household. |
| | **Other: truck** | Indicates whether there are other available trucks (besides those for which the individual is the main driver) in the household. |
| Covariates | ***Socioeconomic and demographic characteristics: individual-level*** | |
| | **Generation*** | Indicates respondents' age by four age groups: (a) 18-34, (b) 35-44, (c) 45-64, and (d) 65 and older. |
| | **Gender*** | Male/female. |
| | **Race: White** | Indicates whether the respondent is White. |
| | **Education** | Indicates the education level of the respondent by three categories: (a) high school or less, (b) some college, and (c) some graduate school. |
| | **Homemaker** | Indicates whether the respondent is a homemaker. |
| | ***Socioeconomic and demographic characteristics: household-level*** | |
| | **Household income*** | Indicates annual household income by three categories: (a) below $50,000, (b) $50,000 to $99,999, and (c) above $100,000. |
| | **Household size*** | Count of household members after excluding non-relatives. The covariate includes three categories: (a) 1, (b) 2, and (c) above 3. |
| | **No. of children** | Count of household members younger than 18 years old. |
| | ***Land use variables*** | |
| | **Neighborhood type*** | This variable is derived from the NHTS variable URBRUR, which only takes on these two values: urbanized and rural. According to NHTS (https://nhts.ornl.gov/faq), "urban areas (UAs) that contain 50,000 or more people and urban clusters (UCs) that contain at least 2,500 people but less than 50,000 people" are considered to be "urbanized"; all other areas are considered to be "rural". As shown in Table 5, 72% of the sample lives in an urbanized area. |
| | ***Travel-related variables*** | |
| | **No. of vehicles as main driver*** | The number of vehicles for which the respondent was reported as the main driver. The variable takes on two values: (a) 1, and (b) above 2. |
| | **Household vehicle-driver ratio** | The ratio of the number of household vehicles to the number of drivers in the household. The variable reflects the sufficiency of the household vehicle ownership. It takes on three values: (a) <1, vehicle-deficit, (b) =1, balanced, and (c) >1, vehicle-surplus. |
| | **Weekly VMD** | Self-reported weekly vehicle-miles driven. |
| | **Share of household-serving trips*** | The share of the individual's trips on the travel diary day that have a purpose of shopping, errands, or transporting people. The variable is derived from the 2017 NHTS travel log. |
| | **Expected household vehicle ownership changes within the next three years** | Takes on four values: (a) decrease vehicles, (b) no change, (c) replace vehicles, keeping the same total, and (d) increase vehicles. The variable is derived from the GDOT survey. |
| | **Personal interest in alternative fuel vehicles** | Indicates personal interest in six types of alternative fuel vehicles: (a) gasoline hybrid, (b) battery electric, (c) flex-fuel, (d) diesel, (e) hydrogen fuel cell, and (f) compressed natural gas. The variable is |

| | |
|---|---|
| | derived from the GDOT survey. |
| **Have used ride-hailing service** | Indicates whether the respondent has used a ride-hailing service before. |
| ***General attitudes*** | |
| **Commute benefit*** | The general attitudes are continuous factor scores extracted from attitudinal statements with five-point Likert-type scale responses. The factor scores are standardized in the original survey dataset, but have not been re-standardized for the sample used in the present study. See Table 7 of the Appendix for item loadings. |
| **Materialistic*** | |
| **Pro-exercise*** | |
| **Pro-vehicle-owning** | |
| **Non-car alternatives** | |
| **Modern urbanite** | |
| **Family/friends-oriented** | |
| ***Targeted marketing*** | |
| **Financial support of societal welfare** | A targeted marketing variable indicating financial support of animal welfare, children's, environmental, wildlife, or international aid causes. We use this variable to indicate the financial involvement and responsibility of the household with respect to societal welfare causes. |
| **Purchase of pet products*** | A targeted marketing variable indicating household purchases of pet products in the last 24 months. The purchases might include actual animals, food, medical supplies, accessories and toys for pets. We use this variable to indicate pet ownership in the household, which might influence the vehicle type preference for transporting pets and pet products. |

* Active covariates.

## 4. METHODOLOGY

Error! Reference source not found. shows the graphical representation of the LCCA model f ramework, which includes two sub-models: the membership model and the measurement model. In the ***membership model***, we use active covariates ($z$) to predict latent class membership, i.e., the nominal (categorical) latent variables $k$. In this study, the covariates include socioeconomic and demographic (SED) characteristics, attitudes, activity patterns, TMD, and land use variables. For the purpose of model parsimony, not all available covariates are used in the membership model; we retain some covariates as inactive, meaning that they do not influence model estimation results but can be used for developing descriptive profiles across clusters. The ***measurement model*** reflects the core differentiating feature of LCCA, i.e., using the latent variable $k$ to account for associations between observed indicators $y$. In this study, we have two groups of indicators (i.e., vehicle types), both drawn from the NHTS[2]. The first group reflects vehicle types for which the respondent was reported as being the main driver, whereas the second group of indicators reflects other available vehicle types (besides those for which the individual is the main driver) in the household. Note that an individual can be listed as the "main driver" for more than one vehicle in the household. Classic LCCA holds the assumption of local independence among indicators, i.e., the indicators are assumed to be mutually independent given cluster membership $k$. In this study, after checking the bivariate residuals between indicators, we relaxed the local independence

[2]We follow the vehicle classification scheme from the 2017 NHTS, which classifies vehicles into seven groups based on body types, i.e., (1) automobile/car/station wagon, (2) van (mini/cargo/passenger), (3) SUV (Santa Fe, Tahoe, Jeep, etc.), (4) pickup truck, (5) other truck, (6) recreational vehicle (RV), and (7) motorcycle/motorbike. We adjust and combine the seven vehicle types into three categories based on data characteristics and modeling needs. Specifically, the three categories are **car** (category (1)), **SUV/van** (categories (2) and (3)), and **truck** (categories (4) and (5)). We do not include categories (6) and (7) due to the low shares (1.0% and 3.1%, respectively) of these two vehicle types.

assumption by allowing associations between the two groups of indicators and within the second group of indicators. The relaxation of the local independence assumption is also in line with the conceptual understanding that household vehicle fleet structures and individual vehicle type choices mutually influence each other. All six indicators are dichotomous (yes/no) variables.

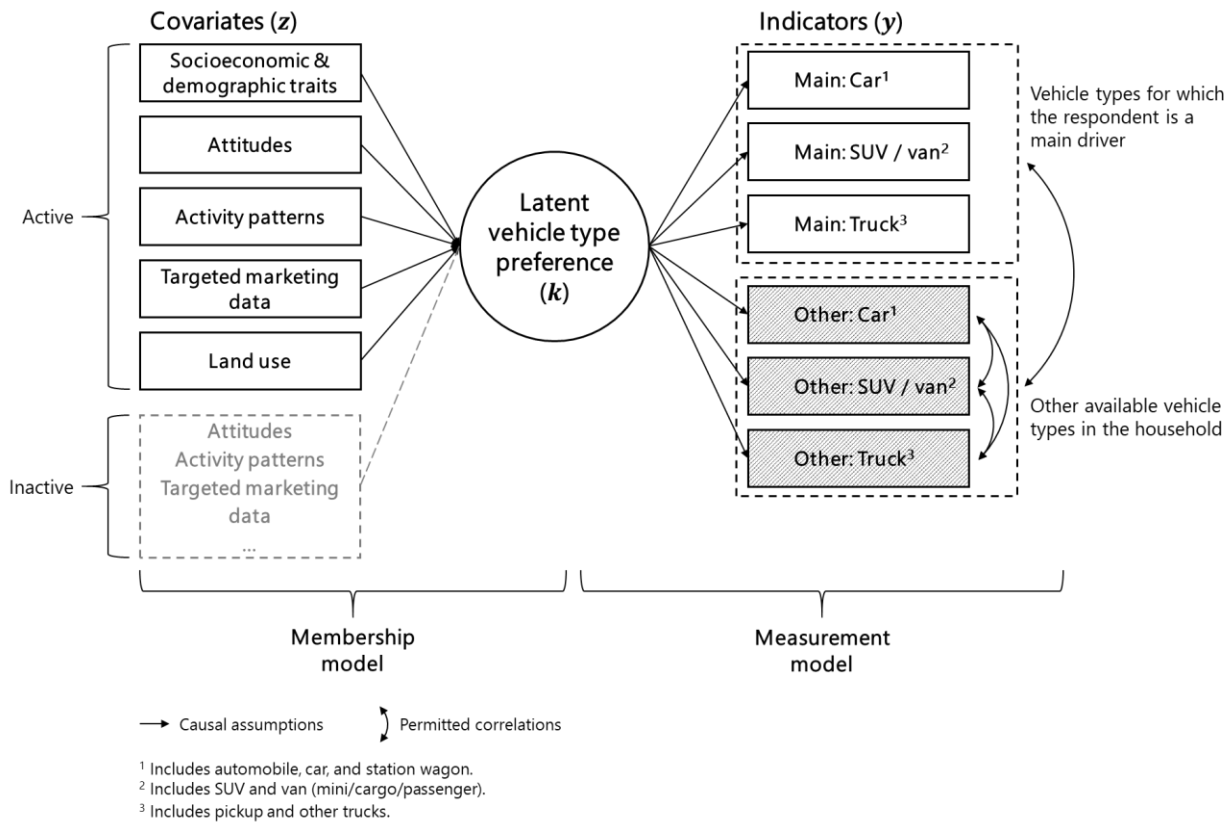


**Figure 1**. **Model framework of the latent class cluster analysis (LCCA)**

In LCCA, the membership and measurement models are estimated simultaneously, enabling both the indicators and the covariates to influence cluster development. Eqs. 1-3 are the mathematical representation of the LCCA model (following the notation in Vermunt and Magidson, 2016).

$$P(\boldsymbol{y}_i|\boldsymbol{z}_i) = \sum_{k=1}^{K} P(k|\boldsymbol{z}_i)\, P(\boldsymbol{y}_i|k) \tag{1}$$

Eq. 1 represents the probability of observing a vector of indicators $\boldsymbol{y}_i$ for individual $i$, given a particular vector of covariates $\boldsymbol{z}_i$. The equation shows how unobserved latent class membership $k$, which has $K$ categories, intervenes between the observed $\boldsymbol{y}_i$ and $\boldsymbol{z}_i$. Specifically, $P(k|\boldsymbol{z}_i)$ is the membership probability for a certain latent class $k$ given the observed covariates $\boldsymbol{z}_i$, and $P(\boldsymbol{y}_i|k)$ is the conditional probability of $\boldsymbol{y}_i$ given the latent class $k$. The next two equations respectively define the constituent probability models of Eq. 1.

$$P(k|\boldsymbol{z}_i) = \frac{\exp\left(\gamma_{k0} + \sum_{r=1}^{R} \gamma_{kr}\, z_{ir}\right)}{\sum_{k'=1}^{K} \exp\left(\gamma_{k'0} + \sum_{r=1}^{R} \gamma_{k'r}\, z_{ir}\right)} \tag{2}$$

Eq. 2 represents the probability that individual $i$ belongs to latent class $k$ given the covariates $\boldsymbol{z}_i$, which is parameterized using the multinomial logit formula. For each latent class, LCCA estimates one intercept $\gamma_{k0}$ and a set of parameters $\gamma_{kr}$ corresponding to the $R$ active covariates.

$$P(\boldsymbol{y}_i = \boldsymbol{m}|k) = \frac{\exp\left[\sum_{t=1}^{6}\left(\beta_{m_t 0}^{t} + \beta_{m_t k}^{t}\right) + \sum_{t<t'} \beta_{m_t m_{t'}}^{tt'}\right]}{\sum_{\boldsymbol{m}' \in M} \exp\left[\sum_{t=1}^{6}\left(\beta_{m'_t 0}^{t} + \beta_{m'_t k}^{t}\right) + \sum_{t<t'} \beta_{m'_t m'_{t'}}^{tt'}\right]} \tag{3}$$

Eq. 3 represents the joint probability of the six dichotomous indicators, also parameterized using the multinomial logit formula. Vectors $\boldsymbol{m}$ and $\boldsymbol{m}'$ represent specific combinations of indicators taking on the values 0 and 1, both of which belong to the set $M$, which contains all possible indicator value combinations (specifically, $2^6 = 64$ possible combinations). Thus, the numerator pertains to a single particular combination of six 0s and 1s (the vector $\boldsymbol{m}$), while the denominator sums over all 64 such combinations. If there were no association between indicators $t$ and $t'$ (i.e., if $\beta_{m_t m_{t'}}^{tt'} = 0$ for all $t \neq t'$), then (1) the sum over $t$ would reflect the product of the terms associated with each individual indicator ($exp\left[\sum_{t=1}^{6}\left(\beta_{m_t 0}^{t} + \beta_{m_t k}^{t}\right)\right] = \prod_{t=1}^{6} exp\left(\beta_{m_t 0}^{t} + \beta_{m_t k}^{t}\right), i.e.\ P(\boldsymbol{y}_i = \boldsymbol{m}|k) = \prod_{t=1}^{6} P(y_{it} = m_t|k)$); and (2) the intercept $\beta_{m_t 0}^{t}$ for indicator $t$ would represent the average propensity, across all latent classes, to take on the value $m_t$. However, in the joint probability expression, this intercept term is adjusted by the last term of the numerator, representing the association between indicators $t$ and $t'$. Since we maintain the local independence assumption for the first three indicators, $\beta^{12}$, $\beta^{13}$, and $\beta^{23}$ are set to zero. Finally, for each latent class $k$, $\beta_{m_t k}^{t}$ represents the class-specific deviation from the average propensity. In this study, $t$ belongs to {1=main: car, 2=main: SUV/van, 3=main: truck, 4=other: car, 5=other: SUV/van, 6=other: truck}.

To select a model that optimizes both fit and interpretability, we investigated LCCA models with varying numbers of classes. Based on the Bayesian Information Criterion (BIC, 5628.98), the model with seven segments is found to be best overall. The parameters of the final model are presented in **TABLE 3** and **TABLE 4**; to interpret the results, we rely on the segment-specific distributions of indicators and covariates. In Section 5.1, we analyze segment-specific distributions of *indicators* to reveal the latent vehicle type propensities, and based on these we interpret and name each segment (**Error! Reference source not found.**). In Section 5.2, we develop and discuss s egment profiles based on the segment-specific distributions of *covariates* (**TABLE 5**).

**Table 3. Coefficients and z-values of the estimated LCCA measurement model (N=1,111)**

| $\beta^t_{m_t0}, \beta^t_{m_tk}$ | **Intercept** | | **Segment 1** *Car-plus* | | **Segment 2** *Mostly car* | | **Segment 3** *SUV/van-plus* | | **Segment 4** *Mostly SUV/van* | | **Segment 5** *Truck-plus* | | **Segment 6** *Mostly truck* | | **Segment 7** *Vehicle-abundant* | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* |
| **Main: car** | | | | | | | | | | | | | | | | |
| Yes | 0.27 | 0.47 | **4.41** | 2.39 | **4.26** | 2.31 | **-4.15** | -2.65 | **-3.63** | -2.34 | **-1.20** | -2.07 | -0.54 | -0.93 | 0.84 | 1.47 |
| **Main: SUV/van** | | | | | | | | | | | | | | | | |
| Yes | 0.02 | 0.05 | **-3.38** | -4.31 | **-1.75** | -4.46 | **3.72** | 2.64 | **3.41** | 2.42 | **-1.86** | -4.03 | -0.37 | -0.96 | 0.24 | 0.63 |
| **Main: truck** | | | | | | | | | | | | | | | | |
| Yes | **-1.93** | -2.28 | -2.87 | -1.17 | -2.61 | -1.06 | -2.52 | -1.02 | -2.37 | -0.96 | **5.13** | 3.36 | **3.40** | 3.64 | **1.84** | 2.23 |
| **Other: car** | | | | | | | | | | | | | | | | |
| Yes | **-1.44** | -11.91 | **0.89** | 4.16 | **-1.23** | -4.44 | **1.25** | 5.58 | **-0.70** | -2.60 | **0.59** | 2.58 | **-2.11** | -4.12 | **1.31** | 7.35 |
| **Other: SUV/van** | | | | | | | | | | | | | | | | |
| Yes | **-2.36** | -5.68 | **1.25** | 1.20 | **-2.03** | -2.61 | **1.63** | 3.56 | -2.47 | -1.13 | **1.65** | 3.64 | -1.66 | -1.76 | **1.68** | 3.91 |
| **Other: truck** | | | | | | | | | | | | | | | | |
| Yes | **-2.19** | -4.35 | 0.39 | 0.40 | **-1.35** | -2.34 | **1.60** | 2.77 | -0.20 | -0.33 | **1.98** | 3.17 | -2.54 | -0.87 | 0.12 | 0.22 |

| $\beta^{tt'}_{m_tm_{t'}}$ | **Other: car** Yes | | **Other: car** No | | **Other: SUV/van** Yes | | **Other: SUV/van** No | | **Other: truck** Yes | | **Other: truck** No | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* |
| **Main: car** | | | | | | | | | | | | |
| Yes | -0.17 | -1.44 | 0.17 | 1.44 | -0.01 | -0.11 | 0.01 | 0.11 | **0.53** | 2.94 | **-0.53** | -2.94 |
| **Main: SUV/van** | | | | | | | | | | | | |
| Yes | -0.18 | -1.69 | 0.18 | 1.69 | -0.12 | -1.15 | 0.12 | 1.15 | 0.21 | 1.24 | -0.21 | -1.24 |
| **Main: truck** | | | | | | | | | | | | |
| Yes | 0.15 | 1.28 | -0.15 | -1.28 | 0.01 | 0.05 | -0.01 | -0.05 | -0.42 | -1.92 | 0.42 | 1.92 |
| **Other: car** | | | | | | | | | | | | |
| Yes | - | - | - | - | **-0.54** | -9.90 | **0.54** | 9.90 | **-0.41** | -7.13 | **0.41** | 7.13 |
| **Other: SUV/van** | | | | | | | | | | | | |
| Yes | - | - | - | - | - | - | - | - | **-0.57** | -7.44 | **0.57** | 7.44 |

Notes:
(1) The bolded coefficients are statistically significant at the 0.05 level.
(2) We used effect coding for model outputs. Given the dichotomous nature of the indicators, we suppress the identical-except-sign-reversed coefficients of the corresponding "No" values for greater readability.

**Table 4. Coefficients and z-values of the estimated LCCA membership model (N=1,111)**

| $\gamma_{k0}, \gamma_{kr}$ | Segment 1 *Car-plus* | | Segment 2 *Mostly car* | | Segment 3 *SUV/van-plus* | | Segment 4 *Mostly SUV/van* | | Segment 5 *Truck-plus* | | Segment 6 *Mostly truck* | | Segment 7 *Vehicle-abundant* | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* | Coef. | *z* |
| **Intercept** | 0.17 | 0.10 | **3.26** | 2.69 | -2.01 | -1.12 | **3.00** | 2.42 | 0.70 | 0.40 | -0.18 | -0.07 | -4.93 | -1.41 |
| ***Socioeconomic and demographic*** | | | | | | | | | | | | | | |
| **Generation** | | | | | | | | | | | | | | |
| 18-34 | -2.17 | -1.46 | 1.27 | 0.91 | **-3.35** | -2.24 | 2.25 | 1.60 | -1.88 | -1.26 | -4.01 | -0.56 | **7.89** | 2.23 |
| 35-44 | **-3.09** | -4.20 | **1.65** | 2.51 | **-2.31** | -3.09 | 1.16 | 1.73 | **-3.85** | -4.69 | 2.56 | 1.04 | **3.88** | 2.32 |
| 45-64 | **6.05** | 5.02 | **-5.75** | -5.02 | **6.34** | 5.24 | **-5.74** | -4.98 | **5.67** | 4.66 | -3.89 | -1.48 | **-2.68** | -1.64 |
| 65+ | -0.78 | -1.03 | **2.83** | 3.17 | -0.68 | -0.85 | **2.34** | 2.56 | 0.07 | 0.09 | **5.33** | 2.12 | **-9.10** | -3.54 |
| **Gender** | | | | | | | | | | | | | | |
| Male | 0.14 | 0.50 | **-0.97** | -3.17 | -0.43 | -1.46 | **-1.02** | -3.25 | **0.85** | 2.74 | **0.92** | 2.48 | 0.53 | 0.70 |
| Female | -0.14 | -0.50 | **0.97** | 3.17 | 0.43 | 1.46 | **1.02** | 3.25 | **-0.85** | -2.74 | **-0.92** | -2.48 | -0.53 | -0.70 |
| **Household income** | | | | | | | | | | | | | | |
| Below $50,000 | **-6.22** | -5.59 | **6.33** | 5.41 | **-7.08** | -6.33 | **5.99** | 5.11 | **-6.35** | -5.65 | **7.26** | 5.79 | 0.07 | 0.06 |
| $50,000 to $99,999 | **1.30** | 2.50 | **1.37** | 2.53 | **1.43** | 2.73 | **1.15** | 2.06 | **1.72** | 3.23 | 0.90 | 1.35 | **-7.88** | -5.15 |
| Above $100,000 | **4.93** | 4.71 | **-7.70** | -5.40 | **5.65** | 5.38 | **-7.14** | -4.98 | **4.63** | 4.39 | **-8.16** | -5.22 | **7.80** | 4.16 |
| **Household size** | | | | | | | | | | | | | | |
| 1 | **-19.33** | -4.68 | **22.39** | 5.78 | **-19.13** | -4.60 | **21.73** | 5.60 | **-17.85** | -4.32 | **23.61** | 6.01 | **-11.42** | -2.42 |
| 2 | **8.79** | 4.33 | **-11.46** | -5.63 | **8.37** | 4.07 | **-12.39** | -6.04 | **8.12** | 4.00 | **-11.82** | -5.76 | **10.39** | 3.57 |
| 3+ | **10.54** | 4.91 | **-10.93** | -5.73 | **10.76** | 5.01 | **-9.34** | -4.89 | **9.72** | 4.51 | **-11.79** | -5.72 | 1.03 | 0.44 |
| ***Land use*** | | | | | | | | | | | | | | |
| **Neighborhood type**[1] | | | | | | | | | | | | | | |
| Urbanized area | **0.58** | 2.16 | -0.56 | -1.48 | -0.22 | -0.79 | **-0.85** | -2.17 | **-0.79** | -2.77 | **-2.12** | -4.78 | **3.96** | 3.79 |
| Rural area | **-0.58** | -2.16 | 0.56 | 1.48 | 0.22 | 0.79 | **0.85** | 2.17 | **0.79** | 2.77 | **2.12** | 4.78 | **-3.96** | -3.79 |
| ***Travel-related*** | | | | | | | | | | | | | | |
| **No. of vehicles as main driver** | | | | | | | | | | | | | | |
| 1 | **6.23** | 5.51 | 1.13 | 1.50 | **7.95** | 6.20 | **2.21** | 2.83 | **5.03** | 4.43 | -0.37 | -0.48 | **-22.16** | -4.74 |
| 2+ | **-6.23** | -5.51 | -1.13 | -1.50 | **-7.95** | -6.20 | **-2.21** | -2.83 | **-5.03** | -4.43 | 0.37 | 0.48 | **22.16** | 4.74 |
| **Share of household-serving trips** | **-10.31** | -5.08 | **10.44** | 5.18 | **-10.12** | -4.98 | **9.11** | 4.46 | **-10.02** | -4.93 | **8.97** | 4.31 | 1.94 | 0.85 |
| ***General attitudes*** | | | | | | | | | | | | | | |
| **Commute benefit** | **-1.68** | -3.28 | **2.94** | 4.26 | **-1.65** | -3.17 | **2.89** | 4.14 | **-1.93** | -3.74 | **3.34** | 4.75 | **-3.91** | -4.53 |
| **Materialistic** | **2.66** | 5.22 | **-2.24** | -4.66 | **2.82** | 5.46 | **-1.82** | -3.94 | **2.77** | 5.32 | **-2.21** | -4.27 | **-1.88** | -2.34 |
| **Pro-exercise** | **0.93** | 3.00 | **-1.94** | -5.38 | **0.92** | 2.90 | **-2.05** | -5.57 | **1.59** | 4.69 | **-1.84** | -4.66 | **2.39** | 2.76 |
| ***Targeted marketing*** | | | | | | | | | | | | | | |
| **Financial support of societal welfare** | | | | | | | | | | | | | | |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Yes | **-1.08** | -3.24 | **-0.62** | -1.96 | **-1.27** | -3.69 | -0.42 | -1.25 | **-1.25** | -3.61 | -0.00 | -0.01 | **4.63** | 4.52 |
| No | **1.08** | 3.24 | **0.62** | 1.96 | **1.27** | 3.69 | 0.42 | 1.25 | **1.25** | 3.61 | 0.00 | 0.01 | **-4.63** | -4.52 |
| **Purchase pet products** | | | | | | | | | | | | | | |
| Yes | -0.63 | -0.90 | **-2.81** | -3.06 | -0.28 | -0.40 | **-2.36** | -2.54 | -0.21 | -0.29 | **-3.22** | -3.19 | **9.51** | 3.84 |
| No | 0.63 | 0.90 | **2.81** | 3.06 | 0.28 | 0.40 | **2.36** | 2.54 | 0.21 | 0.29 | **3.22** | 3.19 | **-9.51** | -3.84 |

Note: The bolded coefficients are statistically significant at the 0.05 level. See TABLE 2 for variable definitions.

### 5.1 Identification of Latent Classes

Error! Reference source not found. illustrates the segment-specific distributions for each of the six i ndicators (i.e., the respective proportions of segment members that are main drivers or other drivers for each of the three vehicle types), and at the top of each segment shows the weighted share of the sample falling within that segment. The segment-specific proportions are represented by the heights of bars and the dotted lines represent the average shares of indicators across the sample, allowing for a comparison of the overall sample with corresponding segment-specific shares and thus giving a visual understanding of each segment relative to the average. Specifically, **Error! Reference source not found.(a)** shows the three segment-specific vehicle type shares (i.e., car, SUV/van, and truck) for the vehicle(s) for which the respondent was the main driver, while **Error! Reference source not found.(b)** shows the segment-specific vehicle type shares for other available vehicles in the household (i.e., vehicles that are present in the household, but for which the respondent is not the main driver). Note that respondents can be the main driver of multiple vehicles, so the sum of vehicle type proportions in each segment may exceed one. Next, based on the segment-specific vehicle type shares shown in **Error! Reference source not found.**, we d iscuss and name each latent segment.

**Segment 1** is the largest segment and comprises 26% of the total number of respondents in the sample. Almost all Segment 1 members are main drivers of cars only; however, we see that their households have other vehicles. For the other household vehicles, the proportions of the three vehicle types are all above the sample average. We may interpret this to indicate that many of these respondents have another vehicle in the household available for use. Reflective of having other vehicles available, we name Segment 1, "**car-plus**."

**Segment 2** is the second largest segment, comprising 23% of the respondents in the sample. Similar to Segment 1, almost all Segment 2 members are main drivers of cars only, with the exception of 4% who are also main drivers of SUVs/vans. The defining difference between Segments 1 and 2 is that most members of Segment 2 do not have other available vehicles in their households. For them, the vehicles they drive are the only vehicles available to both themselves and their households (when applicable, i.e., for respondents with additional household members). Thus, we name Segment 2, "**mostly car**."

**Segment 3** comprises 14% of respondents in the sample. Members of this segment are main drivers for SUVs/vans only. Similar to Segment 1, Segment 3 members also have other available household vehicles, and the proportions of the three vehicle types otherwise available to be driven are all above the sample averages. Accordingly, we name Segment 3, "**SUV/van-plus**."

**Segment 4** comprises 10% of respondents in the sample. Like Segment 3, members of Segment 4 are only main drivers of SUVs/vans, with the defining difference being that most of these households do ***not*** have other available vehicles. As such, we name Segment 4, **"mostly SUV/van**."

**Segment 5** comprises 9% of respondents, and members from this segment are main drivers of trucks only. However, respondents in this segment have other vehicles in the household that may be available to them, and for these other household vehicles, the proportions of the car and SUV/van vehicle types are above the sample average. Thus, we name Segment 5, "**truck-plus**."

**Segment 6** comprises 8% of respondents. Almost every member of this segment is a main driver of trucks, while there are non-negligible proportions of members who are also main drivers of cars and SUVs/vans. Additionally, members of this segment do not have other household vehicles available to them (as non-main drivers). As such, to maintain the parallel structure developed thus far, we name this segment, "**mostly truck**."

**Segment 7** comprises 10% of the respondents in the sample. Compared to the sample averages, members in this segment are main drivers for relatively high proportions of all three vehicle types. By summing the proportions of members associated with the three vehicle types, obtaining 1.93, we can conclude that people in this segment tend to be main drivers for multiple vehicle types. Moreover, a large proportion of members of this segment also have other available vehicles in their households. As such, we name Segment 7, **"vehicle-abundant**."

Thus, we see an inherent hierarchical structure emerging from the data, whereby across the three vehicle types studied, we have individuals who are primary drivers of either car, SUV/van, or truck while having other vehicle types available to them in the household (i.e., the car, SUV/van, truck "**plus"** segments). Parallel to this, there are individuals for whom the only vehicle available is primarily the one they drive, with low proportions of these respondents having other vehicles available (the car, SUV/van, and truck "**mostly**" segments). The seventh segment stands alone, with respondents in this segment often appearing to be main drivers for multiple vehicles, while also tending to have other vehicles available in the household ("**vehicle-abundant**").

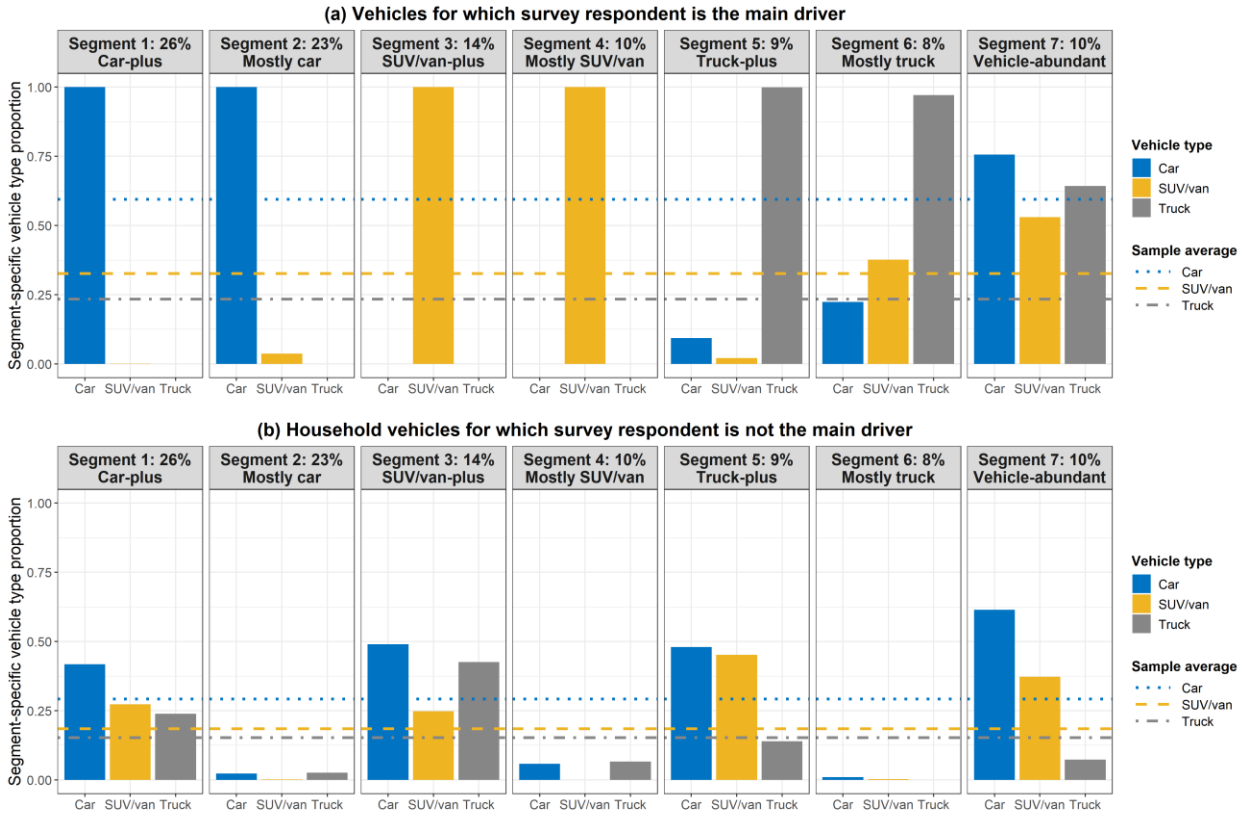


**Figure 2. Segment-specific proportions for each vehicle type indicator (N=1,111)**

## 5.2 Segment Profiles

In this section, we develop a profile for each of the seven previously-discussed vehicle type propensity segments, using the active and inactive covariates (**TABLE 5)**. Specifically, we examine the central tendencies of each segment with respect to individual-level characteristics such as gender, age, and education; household-level characteristics such as household income and size; land-use and travel-related preferences ranging from neighborhood type to future travel behaviors/interests; general and travel-related attitudes such as views on exercise, spending, and

commute benefits; and TMD-derived behaviors such as charitable spending and pet-related purchases. We use posterior class membership probabilities (Eq. (4)) to estimate segment-specific shares/means for nominal/continuous covariates (Eqs. (5a) and (5b), respectively, where $w_i$ is the case weight) (Vermunt and Magidson, 2016). The posterior class membership is conditioned on both covariates and indicators, which fully utilizes the information from the data. In addition, with the application of weights in modeling and profile generation, user profiles are representative of Georgia residents.

$$\hat{P}(k|\boldsymbol{z}_i, \boldsymbol{y}_i) = \frac{\hat{P}(k|\boldsymbol{z}_i)\hat{P}(\boldsymbol{y}_i|k, \boldsymbol{z}_i)}{\hat{P}(\boldsymbol{y}_i|\boldsymbol{z}_i)}, \tag{4}$$

$$\hat{P}(z_{ir} = a|k) = \frac{\sum_{z_{ir}=a} w_i \hat{P}(k|\boldsymbol{z}_i, \boldsymbol{y}_i)}{\sum_i w_i \hat{P}(k|\boldsymbol{z}_i, \boldsymbol{y}_i)}, \tag{5a}$$

$$\hat{E}(z_{ir}|k) = \frac{\sum_i z_{ir} w_i \hat{P}(k|\boldsymbol{z}_i, \boldsymbol{y}_i)}{\sum_i w_i \hat{P}(k|\boldsymbol{z}_i, \boldsymbol{y}_i)}. \tag{5b}$$

The **car-plus** segment (main drivers of cars, with other household vehicles available) contains a large proportion of individuals ages 18-34 (27%) relative to other segments (18% in the entire sample). The segment has a more-or-less equal share of males and females and the lowest share of individuals with a high school education or less (19%, compared to 33% sample-wide) among all segments. Accordingly, a large proportion of individuals from this segment have annual household incomes of more than $100,000 (44%, compared to 28% sample-wide). The segment does not have any single-person households. It has the highest share of urbanized area dwellers (87%, compared to 72% sample-wide), which may be why it also has the highest share of individuals who have used ride-hailing services (44%, compared to 33% sample-wide), given that coverage for these services is higher in urban areas. The urbanized environment may similarly contribute to why this segment has the second lowest weekly vehicle-miles driven (VMD, 122.13 mi, compared to 141.82 mi sample-wide). This segment also has the lowest share of household-serving trips (23%, compared to 27% sample-wide). Regarding travel interests, this segment has the highest proportion of individuals who are interested in battery electric vehicles (48%, versus 39%), and the lowest share interested in hydrogen fuel vehicles (11%, versus 15%). Individuals from this segment have mildly negative attitudes towards vehicle ownership (-0.097, versus 0.079 sample-wide) and mildly positive attitudes toward non-car alternatives such as walking, bicycling, and public transit (0.076, versus -0.033) – findings that are in line with the urban residential location choices of many individuals in this segment. Overall, we see that the **car-plus** segment appears to consist primarily of individuals from two-or-more-person affluent households, who choose to live in more accessible locations, and who, in general, have relatively low travel demands and a small share of household-serving trips.

The **mostly car** segment (main drivers of cars who mostly do not have other household vehicle options) contains more females (68%, versus 51%) and the lowest share of whites (49%, versus 69%), relative to the other segments. Sizable majorities of the segment are single householders (71%, versus 28%), from lower-income households (below $50,000, 64% versus 38% sample-wide), and/or residing in urbanized areas (82%). Most of these individuals are the main drivers of one vehicle (85%). Accordingly, 81% of households are vehicle/driver-balanced,

which is the highest share among segments (63% overall). Regarding future vehicle ownership, a relatively low proportion of individuals from this segment are seeking new vehicles (36% want to either replace current vehicles or own more, versus 46% overall). Compared to other segments, a larger proportion of individuals is interested in hydrogen fuel cell vehicles (19%, versus 15%) while the segment contains a relatively low proportion of individuals who are interested in diesel vehicles (8%, versus 17%). The segment has the lowest weekly VMD (120.66 mi); however, it has the largest share of household-serving trips (32%), both of which may be due in part to the high share of single-person households. Individuals from this segment are the least materialistic (-0.221, versus 0.016 sample-wide) and the least family/friends-oriented (-0.306, versus -0.059 sample-wide) among all segments. They also have the most negative attitudes toward vehicle ownership (-0.124). Compared to the sample average, individuals from this segment have the lowest proportion of societal welfare involvement (21% versus 28% sample-wide) and are unlikely to own pets (5%, versus 9% sample-wide). In general, the **mostly car** segment primarily constitutes single individuals, who are neither family/friends-oriented nor societal-welfare-involved, from lower-income households with low overall travel demand relative to other segments.

The **SUV/van-plus** segment (main drivers of SUVs/vans, with other household vehicles available), has the largest share of individuals in the 35-44 (31%, versus 19% sample-wide) and 45-64 (49%, versus 43% sample-wide) age groups. The majority of this segment is female (75%) and/or white (81%), and it has the largest share of highly educated people (30%, versus 16% sample-wide). It also has the largest share of high-income (above $100,000, 55%) and large (3+, 63%, versus 34% sample-wide) households. Accordingly, individuals from this segment have the highest number of children (0.95, versus 0.52 sample-wide), the highest share of homemakers (21%, versus 10%), and the second highest share of pet owners (16%, versus 9%). Regarding travel behavior, individuals in the **SUV/van-plus** segment are main drivers of only one vehicle (i.e., highly likely to be an SUV/van). Even though only 8% of individuals in this segment are from vehicle-deficit households, 15% are planning to own more vehicles, which is the largest share among all segments (9% overall). Meanwhile, the segment also has the strongest interest in vehicle replacement (44%). Its mean weekly VMD is relatively high (160.09 mi). The general attitudes show that individuals in this segment are relatively materialistic (0.151), enjoy owning vehicles (0.286), prefer modern urbanite lifestyles (0.141), and are the most family/friends-oriented (0.249). Generally, we see that individuals from the **SUV/van-plus** segment are primarily family-oriented females in large, affluent households, who are heavy travelers (based on weekly VMD), and have relatively strong interest in vehicle ownership.

The **mostly SUV/van** segment (main drivers of SUV/van vehicle types, mostly without other household vehicle options) contains a large share of young individuals, specifically, the largest share of individuals ages 18-34 (28%) and the second largest share of individuals ages 35-44 (27%). Like the **SUV/van-plus** segment, this segment has a high share of females (76%) but contrastingly has the highest share of low-income households (below $50,000, 68%). Interestingly, the household size distribution is bipolar – the segment contains 52% single-person households and 40% large households (compared to 28% and 34%, respectively, sample-wide). Accordingly, the segment contains the largest share of vehicle-deficit households (17%, versus 7%) and the lowest share of vehicle-surplus households (4%, versus 30%), given that most individuals in the segment are main drivers of only one vehicle (93%). Nonetheless, individuals from this segment have very strong propensities toward owning vehicles (0.329) with negative attitudes towards non-car alternatives (-0.154). A plausible explanation may be that low household incomes restrict desired vehicle ownership behavior and thus results in the inconsistency between vehicle

ownership attitudes and behaviors. On the other hand, we also see the possibility that unsatisfied vehicle ownership propensities may contribute to increased desires for owning vehicles. In terms of other general attitudes, these individuals have the most positive attitudes towards commuting (0.345, versus 0.056 sample-wide), the most negative attitudes towards exercise (-0.355, versus -0.097 sample-wide), and higher preferences for an urbanite lifestyle relative to other segments (0.303, versus 0.023 sample-wide). Although the latter result may be somewhat unexpected, it is consistent with previous studies such as Choo and Mokhtarian (2004). Overall, we see that the **mostly SUV/van** segment mainly consists of younger females, with low household incomes, who either live alone or live in large households. They have a strong desire to own vehicles, while many of them are from vehicle deficit-households.

The **truck-plus** segment (individuals who are main drivers of trucks, with other household vehicles available), contains the smallest share of individuals ages 35-44 (4%), with average (44%) or higher-than-average (33%, where the sample average is 20%) proportions of individuals in the 45-64 and 65+ age groups, respectively. This segment is dominated by males (87%), whites (87%), and less-educated individuals (47%) who do not live alone, and who are from middle-income households ($50,000 to $99,999, 54%). It contains the largest share of rural dwellers (61%, versus 28% sample-wide). Regarding travel behavior, a large share of individuals in this segment have vehicle replacement plans (44%). Sizable shares show interest in diesel vehicles (33%, versus 17%) and hydrogen fuel cell vehicles (20%, the largest share among segments), whereas the segment has a relatively small share of individuals showing interest in gasoline hybrid vehicles (32%, versus 41%). With respect to general attitudes, individuals in this segment are the most materialistic (0.246) and exercise-oriented (0.296). They have the most negative attitudes towards commuting (-0.145) and modern urbanite lifestyles (-0.334). Overall, the **truck-plus** segment primarily constitutes white males with relatively low education levels and medium household incomes, who are materialistic and live in rural areas.

The **mostly truck** segment (main drivers of trucks, non-negligible proportions of whom are also main drivers of cars and/or SUVs/vans) contains a large share of individuals who are main drivers for more than one vehicle (61%, versus 24% overall), as well as a large share of vehicle-surplus households (54%, versus 30%). This segment does not contain any 18-34-year-olds, but has the largest share of individuals ages 65 and over (44%). This segment is dominated by males (87%), whites (81%), less-educated individuals (71%, the largest share among segments), lower-income households (66%), and single householders (77%). In keeping with its age and average household size, this segment does not have any children living at home. Similar to the **truck-plus** segment, the majority are from rural areas (58%). Most individuals in this segment are satisfied with their current household vehicle fleet structure and thus do not plan to make any changes (69%). Compared to other segments, this segment has the largest share of individuals interested in flex-fuel (33%, versus 25% sample-wide) and compressed natural gas (CNG, 19%, versus 11% sample-wide) vehicles. It has a high weekly VMD (162.01 mi) and a high share of household-serving trips (32%) – probably due to the dominance of single-person households. This segment also has the lowest share of individuals with ride-hailing experience (4%) and the most negative attitudes toward non-car alternatives (-0.305). Individuals from this segment have relatively high propensity toward financially support societal welfare and are the least likely to own pets. Overall, the **mostly truck** segment primarily comprises single, less-educated, lower-income, older males, who live in rural regions and have above-average travel demand.

The **vehicle-abundant** segment (main drivers for multiple vehicle types, many of whom also have other vehicles available) unsurprisingly has the largest share (99%) of households with

more than one vehicle per driver, and 19% of its members plan to reduce the number of household vehicles owned (compared to 8% sample-wide). This segment has a large proportion of people ages 45-64 (48%, versus 43%). It is overwhelmingly male (72%), and has the largest share of whites (88%). A large share of members are from high-income (49%), two-person (69%, versus 38% sample-wide) households – there are no single householders in this segment. On the other hand, this segment has a rather negative family/friends-oriented attitude, on average (-0.242), despite having only slightly below the average number of children (0.46, versus 0.52 sample-wide). Regarding travel behavior, individuals in this segment have the highest weekly VMD (199.34 mi) and the strongest favorability toward vehicle ownership (0.377). This segment has the largest shares of individuals who are interested in gasoline hybrid (48%) and diesel (38%) vehicles across all segments, but the smallest share of individuals interested in flex-fuel vehicles (19%). The segment also contains the largest shares of individuals who financially support societal welfare (48%) and who are most likely to own pets (18%). In general, the **vehicle-abundant** segment primarily constitutes men from higher-income, two-person households, who travel heavily and may share or divide the household-serving trips with their partner, and who are likely to support societal welfare financially.

**Table 5. Segment-specific shares/means of covariates (N=1,111)**

| Segments | Car-plus | Mostly car | SUV/van-plus | Mostly SUV/van | Truck-plus | Mostly truck | Vehicle-abun-dant | *Sample* |
|---|---|---|---|---|---|---|---|---|
| **Weighted share** | 0.26 | 0.23 | 0.14 | 0.10 | 0.09 | 0.08 | 0.10 | *1.00* |
| **Unweighted share** | 0.22 | 0.23 | 0.14 | 0.10 | 0.09 | 0.10 | 0.12 | *1.00* |
| ***Socioeconomic and demographic: individual*** | | | | | | | | |
| **Generation*** | | | | | | | | |
| 18-34 | 0.27 | 0.16 | 0.12 | **0.28** | 0.19 | 0.00 | 0.15 | *0.18* |
| 35-44 | 0.13 | 0.24 | **0.31** | 0.27 | 0.04 | 0.09 | 0.18 | *0.19* |
| 45-64 | 0.48 | 0.36 | **0.49** | 0.30 | 0.44 | 0.47 | 0.48 | *0.43* |
| 65+ | 0.12 | 0.24 | 0.08 | 0.15 | 0.33 | **0.44** | 0.19 | *0.20* |
| **Gender*** | | | | | | | | |
| Male | 0.51 | 0.32 | 0.25 | 0.24 | **0.87** | **0.87** | 0.72 | *0.49* |
| Female | 0.49 | 0.68 | 0.75 | **0.76** | 0.13 | 0.13 | 0.28 | *0.51* |
| **Race: White** | 0.63 | 0.49 | 0.81 | 0.74 | 0.87 | 0.81 | **0.88** | *0.69* |
| **Education** | | | | | | | | |
| High school or less | 0.19 | 0.36 | 0.25 | 0.29 | 0.47 | **0.71** | 0.37 | *0.33* |
| Some college | **0.58** | 0.54 | 0.45 | 0.54 | 0.48 | 0.26 | 0.53 | *0.51* |
| Some graduate school | 0.23 | 0.10 | **0.30** | 0.17 | 0.05 | 0.03 | 0.10 | *0.16* |
| **Homemaker** | 0.12 | 0.08 | **0.21** | 0.17 | 0.05 | 0.00 | 0.05 | *0.10* |
| ***Socioeconomic and demographic: household*** | | | | | | | | |
| **Household income*** | | | | | | | | |
| Below $50,000 | 0.22 | 0.64 | 0.13 | **0.68** | 0.19 | 0.66 | 0.23 | *0.38* |
| $50,000 to $99,999 | 0.34 | 0.33 | 0.32 | 0.27 | **0.54** | 0.30 | 0.28 | *0.34* |
| Above $100,000 | 0.44 | 0.03 | **0.55** | 0.05 | 0.27 | 0.04 | 0.49 | *0.28* |
| **Household size*** | | | | | | | | |
| 1 | 0.00 | 0.71 | 0.00 | 0.52 | 0.00 | **0.77** | 0.00 | *0.28* |
| 2 | 0.57 | 0.16 | 0.37 | 0.08 | 0.58 | 0.18 | **0.69** | *0.38* |
| 3+ | 0.43 | 0.13 | **0.63** | 0.40 | 0.42 | 0.05 | 0.31 | *0.34* |
| **No. of children†** | 0.61 | 0.28 | **0.95** | 0.81 | 0.42 | 0.00 | 0.46 | *0.52* |
| ***Land use*** | | | | | | | | |
| **Neighborhood type*** | | | | | | | | |
| Urbanized area | **0.87** | 0.82 | 0.69 | 0.81 | 0.39 | 0.42 | 0.61 | *0.72* |
| Rural area | 0.13 | 0.18 | 0.31 | 0.19 | **0.61** | 0.58 | 0.39 | *0.28* |
| ***Travel-related*** | | | | | | | | |
| **No. of vehicles as main driver*** | | | | | | | | |
| 1 | 0.94 | 0.85 | **1.00** | 0.93 | 0.68 | 0.39 | 0.00 | *0.76* |
| 2+ | 0.06 | 0.15 | 0.00 | 0.07 | 0.32 | 0.61 | **1.00** | *0.24* |
| **Household vehicle-driver ratio** | | | | | | | | |
| <1: vehicle-deficit | 0.09 | 0.05 | 0.08 | **0.17** | 0.09 | 0.06 | 0.00 | *0.07* |
| =1: balanced | 0.76 | **0.81** | 0.63 | 0.79 | 0.49 | 0.40 | 0.01 | *0.63* |
| >1: vehicle-surplus | 0.15 | 0.14 | 0.29 | 0.04 | 0.42 | 0.54 | **0.99** | *0.30* |
| **Weekly VMD†** | 122.13 | 120.66 | 160.09 | 132.22 | 156.05 | 162.01 | **199.34** | *141.82* |
| **Share of household-serving trips*†** | 0.23 | **0.32** | 0.27 | 0.28 | 0.24 | **0.32** | 0.26 | *0.27* |
| **Expected household vehicle ownership changes within the next three years** | | | | | | | | |
| Decrease vehicles | 0.06 | 0.06 | 0.08 | 0.10 | 0.11 | 0.05 | **0.19** | *0.08* |
| No change | 0.46 | 0.58 | 0.33 | 0.38 | 0.38 | **0.69** | 0.30 | *0.46* |
| Replace vehicles, keeping the same total | 0.39 | 0.30 | **0.44** | 0.39 | **0.44** | 0.21 | 0.43 | *0.37* |
| Increase vehicles | 0.09 | 0.06 | **0.15** | 0.12 | 0.07 | 0.05 | 0.08 | *0.09* |
| **Personal interest in alternative fuel vehicles** | | | | | | | | |
| Gasoline hybrid | 0.43 | 0.41 | 0.43 | 0.42 | 0.32 | 0.31 | **0.48** | *0.41* |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Battery electric | **0.48** | 0.41 | 0.42 | 0.31 | 0.32 | 0.23 | 0.30 | *0.39* |
| Flex-fuel | 0.22 | 0.26 | 0.29 | 0.22 | 0.29 | **0.33** | 0.19 | *0.25* |
| Diesel | 0.15 | 0.08 | 0.14 | 0.07 | 0.33 | 0.21 | **0.38** | *0.17* |
| Hydrogen fuel cell | 0.11 | 0.19 | 0.12 | 0.16 | **0.20** | 0.17 | 0.15 | *0.15* |
| Compressed natural gas | 0.12 | 0.13 | 0.11 | 0.02 | 0.09 | **0.19** | 0.13 | *0.11* |
| **Have used ride-hailing service** | **0.44** | 0.29 | 0.42 | 0.38 | 0.20 | 0.04 | 0.29 | *0.33* |
| ***General attitudes*** | | | | | | | | |
| **Commute benefit**[*†] | -0.099 | 0.204 | 0.027 | **0.345** | -0.145 | 0.212 | -0.074 | *0.056* |
| **Materialistic**[*†] | 0.078 | -0.221 | 0.151 | 0.035 | **0.246** | -0.060 | 0.048 | *0.016* |
| **Pro-exercise**[*†] | 0.114 | -0.205 | -0.098 | -0.355 | **0.296** | -0.341 | -0.324 | *-0.097* |
| **Pro-vehicle-owning**[†] | -0.097 | -0.124 | 0.286 | 0.329 | 0.241 | 0.036 | **0.377** | *0.079* |
| **Non-car alternatives**[†] | **0.076** | 0.065 | -0.142 | -0.154 | -0.110 | -0.305 | 0.017 | *-0.033* |
| **Modern urbanite**[†] | 0.070 | 0.077 | 0.141 | **0.303** | -0.334 | -0.138 | -0.203 | *0.023* |
| **Family/friends-oriented**[†] | -0.007 | -0.306 | **0.249** | -0.018 | 0.064 | -0.006 | -0.242 | *-0.059* |
| ***Targeted marketing*** | | | | | | | | |
| **Financial support of societal welfare**[*] | 0.24 | 0.21 | 0.26 | 0.24 | 0.30 | 0.39 | **0.48** | *0.28* |
| **Purchase pet products**[*] | 0.08 | 0.05 | 0.16 | 0.08 | 0.11 | 0.03 | **0.18** | *0.09* |

Note: The numbers in this table represent expected values for the segment, computed with posterior class membership probabilities. Bolded numbers are the maximum segment-specific shares/means across the seven segments, whereas the underlined numbers are the minimum segment-specific shares/means across the seven segments. See TABLE 2 for variable definitions.

[*] Active covariates.

[†] Segment-specific means.

## 6. DISCUSSION

In the prior section, we discussed the composition and characteristics of each vehicle type propensity segment. In this section, we focus on several perspectives that have potential transportation policy implications, namely, household mobility needs and gender differences, vehicle ownership (attitudes versus behaviors), and alternative fuel preferences.

### 6.1 Household Mobility Needs and Gender Differences

Vehicle type choice is a joint outcome of many factors such as budget, personal tastes, and mobility needs. In this section, we speculate on the dominant reasons for vehicle type choices from a perspective of balancing personal tastes and household mobility needs, which will bring a discussion regarding within-household gender differences. As such, we categorize the seven vehicle type propensity segments based on gender and household size (**TABLE 6**) and compare the share of household-serving trips (HST) across segments (**FIGURE 3**).

As confirmed by the literature, as well as by this study, males and females have different propensities with regard to vehicle types. Results show that females have higher propensities for using car or SUV/van vehicle types relative to trucks. This choice is consistent regardless of whether females have other vehicle options in the household or not. Specifically, there are three female-dominated segments: **mostly car**, **mostly SUV/van**, and **SUV/van-plus** (**TABLE 6**). Since we find a bipolar household size distribution in the **mostly SUV/van** segment and hypothesize potential differences in motivation for the two groups of individuals in choosing SUVs/vans, we separate the **mostly SUV/van** segment into **mostly SUV/van: single householder** and **mostly**

**SUV/van: multi-householder** for further analysis. Females account for 64% and 89% of the individuals in the two sub-segments, respectively.

**Table 6. Segment classification by gender and household size**

<table>
<tr><th></th><th>Female-dominated</th><th>Male-dominated</th></tr>
<tr><td rowspan="2">Single-householder-dominated</td><td>Mostly car</td><td rowspan="2">Mostly truck</td></tr>
<tr><td rowspan="2">Mostly SUV/van</td></tr>
<tr><td rowspan="3">Multi-householder-dominated</td><td>Truck-plus</td></tr>
<tr><td>SUV/van-plus</td><td>Vehicle abundant</td></tr>
<tr><td colspan="2">Car-plus</td></tr>
</table>

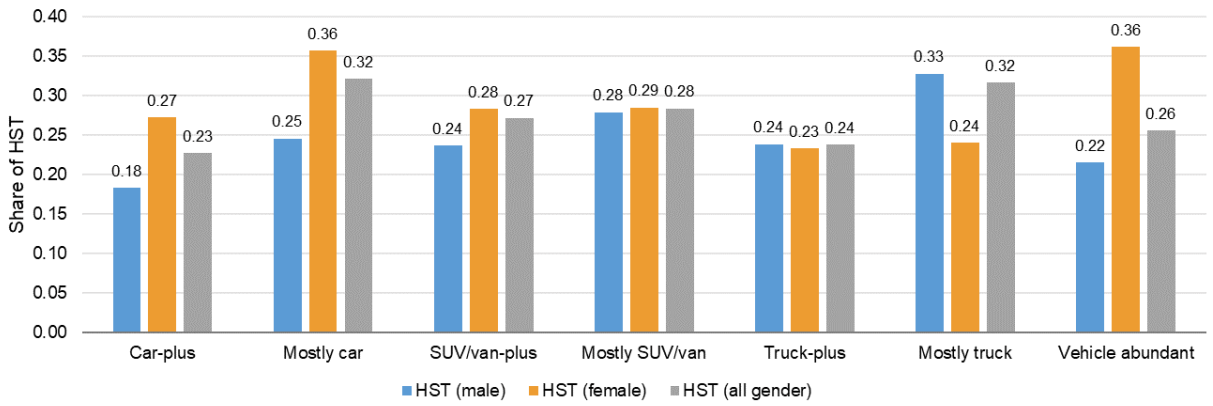


**Figure 3. Share of household-serving trips (HST) by segment and gender**

Given that a large proportion of individuals in the **mostly car** and all individuals in the **mostly SUV/van: single householder** segments live alone, the vehicle type choices can be considered to reflect their individual tastes. Moreover, the **mostly SUV/van: single householder** sub-segment contains a large proportion of individuals ages 18-34 (32%). We can therefore deduce that these young, single women are not choosing SUVs/vans due to household needs such as grocery shopping or transporting children (in fact, the share of HST for this subsegment is only 22%). Instead, they may be choosing SUVs/vans due to their personal preferences regarding vehicle characteristics. For example, a larger vehicle like an SUV may make these women feel safer and/or more in control while driving (Thomas and Walton, 2008). For policymakers interested in emissions reduction policies that encourage smaller, more environmentally friendly vehicles, incentives might be attractive to individuals from this segment, considering their relatively low household-serving needs and relatively low income. From an industrial perspective, this points to the market for so-called "crossover vehicles", which are larger than cars but smaller and lighter (and therefore more fuel-efficient) than most current SUVs.

Regarding the **mostly SUV/van: multi-householder** sub-segment, the SUV/van is very likely to be the only vehicle for these multi-householders (possibly due to limited budgets, as 86% of individuals in this segment have household incomes below $50,000). As such, the vehicle type choice may reflect household needs (e.g., space for transporting both household members and related items such as groceries) more than individual tastes. Supporting this conjecture is the fact that there are 1.71 children per household and 36% of trips made are HST.

Regarding the **SUV/van-plus** segment, the reason for choosing an SUV/van may be a mixture of both household needs and personal preferences. As shown in **Error! Reference source n**

**ot found.(b)**, approximately half of the individuals in this segment have cars available in the household and 43% have trucks available to them. However, individuals from the **SUV/van-plus** segment apparently choose ***not*** to be the main driver for these vehicles. On the one hand, their choices may reflect household needs as opposed to personal preferences, since SUVs/vans may be useful to the homemakers that comprise 21% of the segment. On the other hand, choosing an SUV/van among several available vehicle types in the household may also be interpreted as a personal preference for the vehicle type itself (i.e., similar to those in the **mostly SUV/van: single householder** segment).

In line with conventional expectations and the literature, the three male-dominated segments are **truck-plus**, **mostly truck**, and **vehicle-abundant**. Unsurprisingly, we see that the **truck-plus** segment has a relatively lower proportion of HST (**FIGURE 3**), since the household has other vehicle types that may be more "suitable" for such trips. The **mostly truck** segment has a high proportion of HST (32%), which is common to single-householders and may be related to the household size. Since people from this segment are very likely to live alone, they are responsible for handling household-serving trips independently. Here, we also remind the reader that the **mostly truck** segment is not as pure as the other "mostly" segments. Nonnegligible proportions of individuals from the **mostly truck** segment also drive cars (22%) or SUVs/vans (38%) (**FIGURE 2**), vehicle types that are more "suitable" for HST. In addition, as shown in **FIGURE 3**, males from the **vehicle-abundant** segment have a much lower proportion of HST (22%) than the females from the same segment (36%), which indicates that males in households with access to multiple vehicles may not assume proportional household responsibilities.

The **car-plus** segment has almost equal fractions of males and females. However, males from the **car-plus** segment still have a much lower proportion of HST (18%) relative to females from the same segment (27%). This phenomenon also happens in other segments. As shown in **FIGURE 3**, females usually have a higher proportion of HST relative to males from the same segment, which indicates that females conduct more HST than males, even when they drive the same vehicle type and have similar household vehicle fleet structures.

To summarize, car and SUV/van users are generally dominated by females, whereas truck users are generally dominated by males. Across different segments, female-dominated segments have higher proportions of HST than the male-dominated segments. Even within the same segment, females usually have higher shares of HST than males do. Moreover, people might choose the same vehicle type for different reasons, whether due to personal tastes, household needs, or some combination of the two. The three distinct female user groups of SUVs/vans illustrate this point well. The first group tends to be females from affluent, large households with children (**SUV/van-plus**). They choose an SUV/van for either personal taste or household needs. This "soccer mom" group is the most well-documented SUV/van user group according to previous studies. The second group of the female SUV/van users consists of women tending to be from low-income, large households with children, and the SUV/van is likely to be the only vehicle in the household (**mostly SUV/van: multi-householder**). These female users presumably choose an SUV/van mainly because of household needs. The third female SUV/van user group (**mostly SUV/van: single-householder**) consists mainly of single women, who have low household-serving needs compared to the other two groups of female SUV/van users. For these young, single females, personal tastes might be the dominant reason for them to choose an SUV/van.

### 6.2 Vehicle Ownership Attitudes and Behaviors

The seven vehicle type propensity segments reflect different tastes in vehicle type choices and household vehicle fleet structures, and thus it follows that individuals in these segments may have interesting differences regarding other travel behaviors. In this section, we will focus on vehicle ownership, with respect to the vehicle-owning attitudes and behaviors (i.e., household vehicle-driver ratio).

Individuals from the two car-dominated segments (**car-plus** and **mostly car**) have negative attitudes towards owning vehicles. Consistently, the two segments have more individuals from vehicle-driver balanced households and fewer individuals from vehicle-surplus households, compared to the corresponding sample averages. Specifically, the **car-plus** segment has a much lower proportion of individuals from vehicle-surplus households (15%) relative to the other "plus" segments (**SUV/van-plus**: 29%, **truck-plus**: 42%). Since a large proportion of individuals from the **car-plus** segment have medium/high household incomes, they presumably choose not to own extra vehicles because of their individual preferences/attitudes, rather than the restriction of affordability. In other words, their vehicle ownership behavior is probably (partly) an *outcome* of their disinclined vehicle-owning attitude.

Individuals from the remaining five segments all have positive attitudes towards owning vehicles, with the **vehicle abundant** segment having the most positive attitudes, followed by the two SUV/van segments, and two truck segments. In general, the vehicle ownership behaviors are consistent with the corresponding pro-vehicle-owning attitudes.

The **mostly SUV/van** segment is an exception. Specifically, individuals from the **mostly SUV/van** segment strongly favor owning vehicles (0.329, second highest among segments). However, the segment has the highest proportion of individuals from vehicle-deficit households and the lowest proportion from vehicle-surplus households, which results in an inconsistency with their pro-vehicle-owning attitude. Actually, **mostly SUV/van** segment members from vehicle-deficit households have an even stronger pro-vehicle-owning attitude of 0.488. Apparently, the strong pro-vehicle owning attitude does not result in correspondingly high vehicle ownership. Instead, their unsatisfied vehicle ownership behavior may be (partly) a *cause* of their pro-vehicle-owning attitude, plausibly due to the affordability restriction. Specifically, 68% of individuals in the **mostly SUV/van** segment are from low-income (less than $50,000) households. Given this dissonance between attitude and behavior, people are likely to seek resolution by either changing their behavior (e.g., increasing vehicle ownership), or adjusting their attitudes (Kroesen et al., 2017; Tertoolen et al., 1998). In this case, 12% of individuals from the **mostly SUV/van** segment are planning to increase their numbers of household vehicles over the next three years, substantially more than the sample-wide average of 9%.

In summary, vehicle-owning behaviors are generally consistent with the vehicle-owning attitudes, either pro- or anti-owning vehicles. However, strong pro-vehicle-owning attitudes exist even within households without enough vehicles due to external restrictions such as budgets, suggesting potential vehicle acquisition in the future.

### 6.3 Alternative Fuel Vehicles

In this section, we examine how vehicle type propensities relate to individuals' preferences regarding alternative fuel vehicles. Overall, individuals' preferences for alternative fuel vehicles have a decreasing order as follows: gasoline hybrid, electric battery, flex-fuel, diesel, hydrogen fuel cell, and CNG. In line with intuition, the car- and SUV/van-dominated segments have larger shares of individuals who are interested in gasoline hybrid and battery electric vehicles (BEVs),

whereas the two truck-dominated segments are more interested in flex-fuel, diesel, and hydrogen fuel cell vehicles. On one hand, we see that alternative fuel preferences may be due to mobility needs. For example, BEVs are most suited to short, daily trips in denser areas, i.e., the typical environment for the majority of car- and SUV/van-dominated segments, while for trucks, which are more likely to carry heavy cargo, diesel vehicles are more fuel-efficient and may provide better driving experiences. On the other hand, preferences for alternative fuel types may be moderated by existing market choices, or inversely, individuals may have selected specific vehicle types due to the available fuel types for those choices. For example, in the hybrid and BEV market, car is the dominant vehicle type, whereas in the flex-fuel vehicle market, trucks, especially pickup trucks, play a dominant role (see https://www.eia.gov/renewable/afv/). As such, we conclude that preferences for alternative fuels are jointly affected by daily mobility needs, vehicle type preferences, and available market choices.

In addition, we see that the car, SUV/van, and truck "mostly" segments have lower shares of individuals who are interested in BEVs compared to their "plus" segment counterparts. As shown in **Error! Reference source not found.(b)**, individuals from the "mostly" segments usually h ave no other household vehicles. Thus, it follows that, for the only vehicle in the household, individuals in the "mostly" segments would prefer a more versatile (particularly range-reliable) vehicle that can accommodate all mobility needs, including both daily trips such as commutes, and long-distance trips. Thus, the mileage limits of BEVs in combination with the sparsely available BEV charging facilities in Georgia may discourage BEV interest for individuals who are relying on one vehicle primarily (i.e., the "mostly" segments). In contrast, individuals from the "plus" segments, who usually have multiple available vehicles in their households, may be more favorable toward BEVs as one component of their household vehicle fleet, as BEVs have lower operating costs, are more environmentally friendly, and tend to be considered trendy.

## 7. CONCLUSION

In this study, we applied LCCA to identify seven vehicle type propensity segments, six of which include individuals who reported being the main driver for car, SUV/van, and truck. In three of those segments (**mostly car**, **mostly SUV/van**, and **mostly truck**) this was generally their only available vehicle, while in the other three segments (**car-plus**, **SUV/van-plus**, and **truck-plus**) the "main driver" vehicle was supplemented by other vehicles available in their households. The seventh segment, **vehicle-abundant**, captures survey respondents with multiple main and other household vehicles available. In sum, incorporating the information from the entire household vehicle fleet produced distinctive, interpretable, and meaningful vehicle type propensity segments. We generated user profiles for each segment, detailing segment-specific shares/means for socioeconomic and demographic characteristics, attitudes, land use, travel-related preferences/ behaviors, consumer preferences/behaviors, and activity patterns.

In addition to profiling each vehicle type propensity segment, we further investigated the influence of traditional gender roles on vehicle type propensities. In line with the literature, this study suggested that a large proportion of females drive SUVs/vans due to household responsibilities such as grocery shopping and transporting household members; however, notably, we also identified a group of young females who appear to choose SUVs/vans based on personal preferences. Such preferences are hypothesized to include feelings of increased safety and control accrued from driving a larger vehicle.

We also examined the consistency between vehicle ownership attitude and behavior. In general, vehicle ownership behaviors are consistent with individuals' vehicle owning attitudes. An

exception occurs for individuals who have strongly favorable vehicle owning attitudes but are from vehicle-deficit households in the **mostly SUV/van** segment, whose vehicle ownership behavior is presumably restricted by affordability.

In terms of individuals' interest in alternative fuel vehicles, we see that personal tastes, household mobility needs, and available market choices have varying effects across segments. For example, "plus" segments have higher shares of individuals who are interested in battery electric vehicles (BEVs) relative to their corresponding "mostly" segments, and we conjecture that the latter may prefer a more versatile (particularly range-reliable) vehicle for their household mobility needs. Meanwhile, truck segments have relatively low shares of individuals interested in BEVs compared to the car or SUV/van segments. The reason can be either personal preferences regarding certain vehicle types, or the corresponding BEV type choices in the market (i.e., most BEVs are cars).

In closing, this study provides a unique look at naturally occurring vehicle type segments by examining the influence of individual choices and preferences in combination with household fleet structure and household mobility needs. The novel compilation of data sources and the application of a data-driven vehicle type classification approach provide new insights into relationships between vehicle type propensities and a wide range of general and travel-related attributes that have heretofore not been simultaneously studied.

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# 9. APPENDIX

## Table 7. Attitudinal constructs and strongly-associated statements

| Factor | Statement | Loading |
|---|---|---|
| Commute benefit | My commute is a useful transition between home and work (or school). | 0.677 |
| | My travel to/from work (or school) is usually pleasant. | 0.579 |
| | I wish I could instantly be at work (or school) – the trip itself is a waste of time. | -0.428 |
| Materialistic | I usually go for the basic ("no-frills") option rather than paying more money for extras. | -0.565 |
| | The functionality of a car is more important to me than the status of its brand. | -0.431 |
| | I would/do enjoy having a lot of luxury things. | 0.426 |
| | I like to wait a while rather than being first to buy new products. | -0.357 |
| | I prefer to minimize the amount of things I own. | -0.341 |
| Pro-exercise* | The importance of exercise is overrated. | -0.669 |
| | I am committed to exercising regularly. | 0.663 |
| Pro-vehicle-owning | I definitely want to own a car. | 0.748 |
| | I am fine with not owning a car, as long as I can use/rent one any time I need it. | -0.576 |
| | I like the idea of driving as a means of travel for me. | 0.535 |
| | As a general principle, I'd rather own things myself than rent or borrow them from someone else. | 0.404 |
| Non-car alternatives | I like the idea of walking as a means of travel for me. | 0.666 |
| | I like the idea of bicycling as a means of travel for me. | 0.628 |
| | I like the idea of public transit as a means of travel for me. | 0.336 |
| Modern urbanite | I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood. | 0.417 |
| | My phone is so important to me, it's almost part of my body. | 0.350 |
| Family/friends-oriented* | Family/friends play a big role in how I schedule my time. | 0.612 |
| | It's okay to give up a lot of time with family and friends to achieve other worthy goals. | -0.468 |

* To simplify interpretation, we reversed the directionality of these scales by multiplying the original loadings and factor scores by (-1).