What Type of Vehicles Do Households Own? A Joint Model for Vehicle Body, Vintage, Fuel, and Technology Types

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ABSTRACT
Households' vehicle fleet composition has important policy implications in the area of transport-related energy consumption and emissions. With the recent development in different alternative fuel vehicles (AFVs) such as hybrid and electric vehicles and advanced technology features in the vehicle, the choice dimensions during vehicle purchase are not just limited to vehicle body and age. Households may also consider fuel and technology types. Therefore, this study focuses to investigate households' vehicle type choices, specifically vehicle body, vintage, fuel, and technology types utilizing a survey conducted in British Columbia, Canada. A joint multinomial probit model has been developed that accommodates error correlations across alternatives among the different choice dimensions. The model results confirm significant correlations among the unobserved components. For instance, a significant positive correlation exists between alternative fuel vehicles and vehicles with advanced technology. The study also investigates the effects of households' historical experiences such as historical vehicle fleet composition, and exposure to technology in daily life and vehicles. Historically owning AFVs and advanced technology in vehicles are found to have positive effects on the future preference for vehicles with advanced technology. Transit users and bikers show an inclination towards AFVs, which indicates a need for closer monitoring of the early adopters. The findings of the study provide insights towards targeted marketing to equitably promote the ownership of more sustainable, safer, and fuel-efficient vehicles among diverse age and income groups. Furthermore, the results inform land use and transportation policies to influence vehicle type choices for reducing fuel consumption and emissions.
Keywords: Vehicle type, vintage, fuel type, advanced technology, joint multinomial probit model

INTRODUCTION

Heavy reliance on automobiles results in greater traffic congestion, energy consumption, greenhouse gas (GHG) emissions, traffic collisions, and serious impacts on public health. GHG emissions in the transportation sector are a major concern in North America and around the world. For example, in Canada, the transport sector was second among the major sources accounting for around 22% of the total GHG emissions in 2021 and has seen an increase in GHG emissions by 27% in the last 10 years (Natural Resources Canada, 2023). Passenger cars remain the biggest contributor accounting for 55% of the emissions in the transport sector (Canada's Oil & Natural Gas Producers, 2021). To decarbonize Canada's transportation sector, government agencies have set aggressive targets (e.g., 100% zero-emission vehicle sales by 2035 in the passenger car market (Government of Canada, 2023)) and policies (e.g., incentivizing zero-emission vehicle purchases). To test the effectiveness of these policies and pathways to reach the targets, we need models that are capable of accurately representing the behavior of households regarding the type of vehicle they own and how they utilize it (e.g., vehicle kilometers traveled). Vehicle type choice decision is a crucial one, as it is closely related to individuals' daily travel activity and vehicle utilization which in turn affects vehicular emissions. Tremendous effort has been invested to model vehicle type choice decisions, which has mainly focused on modeling the following dimensions of vehicle type choices: body type (e.g., compact, SUV, etc.) and vintage (i.e., age of the vehicle) (Bhat et al., 2009; Bhat & Sen, 2006; Mohammadian & Miller, 2003; Potoglou & Kanaroglou, 2008). The advancement in new vehicle technologies and the potential environmental benefits of alternative fuel vehicles have introduced newer dimensions to vehicle type choice decisions. For example, households now have the choice to own fully electric and plug-in electric vehicles. Government agencies are offering different monetary benefits such as tax benefits and rebates, which are also contributing to the increasing popularity of such vehicles. For instance, the market penetration of electric vehicles (EVs) in Canada in 2021 (5.3%) has increased by more than four times in the last four years (Canada Energy Regulator, 2022). In addition to the fuel type, the choice of having advanced technologies such as parking assist is increasingly becoming another significant dimension that people are considering given the safety and comfort associated with it. As we are approaching closer to the autonomous vehicle era, understanding the inclination towards more advanced vehicle technology will help to gain insights about the early adopters of such technology. This put forward the need to investigate vehicle technology and fuel type while modeling vehicle type choice decisions.

Therefore, this study investigates households' vehicle type choice decisions considering the following dimensions: body type, vintage, fuel type, and advanced technology features. The choice of these four dimensions might be correlated. For example, someone who is concerned about the environment and their safety might choose a fully electric vehicle as well as choose to have advanced technology. Many of these factors are not observed in the data. Therefore, the modeling exercise needs to recognize the correlations among the unobserved components of these choice dimensions. Ignoring such jointness in the decision may not provide an accurate behavioral representation, resulting in biased model estimation. This study develops a model for households' vehicle type choices assuming it is a joint decision of body, vintage, fuel, and technology type choices. The modeling technique captures the unobserved error correlation among the choice dimensions. Additionally, households' vehicle preferences might be related to their previous experiences such as their exposure to technology both in the vehicles and household and historical vehicle fleet characteristics. Individuals' experience shapes their perception, attitude, and intention to use technology in the future (Saaksjarvi, 2003). For example, households currently and/or previously owning advanced technology in the vehicle might be interested to own such vehicles in the future as they are familiar with the more comfortable and safe driving experience. Also, tech-savvy households owning more technology devices such as laptops, smartphones, google home, etc. might be more inclined towards having advanced technology features. Similarly, households currently owning hybrid/ electric vehicles might appreciate the lower fuel cost and higher environmental benefits offered by the vehicles and thus opt for such vehicles in the future. Therefore, this study explored the effect of historical exposure to technology and vehicle fleet characteristics on households' future vehicle preferences.

LITERATURE REVIEW

The existing literature documents exhaustive efforts to model the choice of different dimensions of vehicle types. For example, Mohammadian & Miller (2003) developed a nested logit model to analyze vehicle type and vintage using data from the Toronto Area Car Ownership Study. The findings of the study suggested that household demographics such as household composition, age, level of education, and occupation, and vehicle characteristics such as vehicle price, performance, and space attributes significantly affect the choices of vehicle type and vintage. Additionally, the study confirmed the presence of significant jointness between the vehicle body and vintage choices in terms of inclusive value parameters. One of the limitations of this nested logit model is that the choice of vehicles was considered as sequential where the body type choice was considered at the upper level and vintage at the bottom. However, vehicle type preferences might not be sequential, rather individuals might consider all the choice dimensions simultaneously. Further studies, such as Baltas & Saridakis (2013) and Spissu et al. (2009) confirmed the effect of household demographics on vehicle type choices. They found that younger and low-income individuals are found to be more inclined towards owning smaller vehicles whereas high-income people are more likely to acquire larger cars such as large sedans and SUVs. In the case of vehicle vintage, Bhat et al. (2009) suggested that high- and medium-income households have a lower preference for older vehicles compared to low-income households.

Paleti et al. (2013) developed a multinomial probit (MNP) model accounting for spatial dependency to investigate vehicle type choices as a combination of body and vintage types. They suggested that households' vehicle type choices are dictated by the accessibility measures such as access to major arterials and collector roads, and access to major employment locations from the household. For example, households with higher access to primary and minor arterial roads were found to be inclined towards newer and smaller cars. Individuals living in high-density areas near the urban core where they have easier access to different destinations (e.g., bus stops, restaurants, shopping malls, etc.) are found to be more inclined towards smaller vehicles such as compact or subcompact cars whereas they are reluctant to own larger vehicles such as vans, pick-up trucks, and SUVs (Chen et al., 2021). Furthermore, the composition of the existing vehicle fleet is also a significant determinant of households' vehicle type preferences. For example, households having a higher number of old subcompact, compact, and midsize/large cars are more inclined towards acquiring new larger vehicles such as SUVs, vans, and trucks (Paleti et al., 2013).

In addition to the vehicle body type and vintage, the fuel type of the vehicle is increasingly becoming another choice dimension for investigation. For instance, Hess et al. (2012) investigated the demand for alternative fuel vehicles among California consumers by jointly modeling vehicle type and fuel type using a cross-nested logit model and found significant correlations between the choice process. The findings of the study also suggested that respondents have a higher baseline preference for alternative fuel vehicles such as clean diesel and hybrid electric vehicles compared to conventional gasoline vehicles when other factors remain the same for all. Khan et al. (2017) explored the demand for alternative fuel vehicles under aggressive policy measures such as a 100% increase in gasoline prices. Under such circumstances, younger individuals having a higher number of vehicles in the household and commuting longer distances are found to be more interested in hybrid/electric vehicles. Similar findings were observed in the case of households with children, and individuals with a higher educational qualification given the fuel cost savings and environmental benefits offered by these vehicles. Household income is also found to be a significant determinant of vehicle fuel type choice where high-income households are more likely to own alternative fuel vehicles due to the higher initial cost of owning (Nazari et al., 2018; Nazari, Mohammadian, et al., 2019). Households' current vehicle fleet composition and vehicle ownership level also significantly affect their decision to own an alternative fuel vehicle. A recent study by Nazari, Rahimi, et al. (2019) revealed that having a battery electric vehicle and a hybrid vehicle in the current vehicle fleet is positively associated with the further acquisition of such vehicles. On the other hand, households with fewer vehicles are found to be reluctant to adopt AFVs due to concerns about their overall reliability (Wang et al., 2022). Finally, the presence of a higher number of charging stations per capita is likely to induce a higher number of electric vehicle adoption (Javid & Nejat, 2017).

The auto industry is witnessing a revolution not only in alternative and clean fuel options but also in advanced technology features in vehicles. As a result, the decision-making process for purchasing a vehicle has become more complex for households. The presence of different advanced technology features in the vehicle such as parking assist, lane-keep assist, emergency braking, blind-spot monitoring, etc. introduces a certain level of driving assistance and can significantly change the overall driving experience as well as reduce driving errors. Hence, consumers might be more attracted to such advanced technology features when purchasing a vehicle. A number of studies explored consumers' preference for advanced vehicle technology which ranges from partial automation to full automation. For instance, Haboucha et al. (2017) investigated the preference for fully autonomous vehicle (AV) technology among the respondents in Israel and North America. The study found that 56% of the respondents were interested in AVs among which younger and highly-educated individuals were found to be the earliest adopters of AVs. Another study by Hossain & Fatmi (2022) investigated individuals' preferences for different levels of vehicle automation and found that their previous exposure to technology significantly affects their preference for higher automation. However, only a handful of studies consider the preference for vehicle technology along with other vehicle type choice dimensions. For instance, Shin et al. (2015) investigated consumers' preferences for advanced vehicle technology and fuel types utilizing a stated preference survey conducted in South Korea. The study revealed a significant positive relationship between the presence of advanced technology in the vehicle and the preference for alternative fuel vehicles such as hybrid and or electric vehicles.

Although the majority of the existing studies considered either vehicle type and vintage (Bhat et al., 2009; Mohammadian & Miller, 2003; Paleti et al., 2013) or vehicle type and fuel type (Hess et al., 2012) together while modeling households' vehicle type choices, very few studies considered advanced vehicle technology in their modeling framework. As driving assistance technology develops, more and more advanced technology features are added to cars, paving the way for fully autonomous vehicles. The availability of such technology features might be another choice dimension for households while making decisions to own a vehicle. During vehicle type choice decisions, households consider all the choice dimensions of vehicle body type, vintage, fuel type, and advanced technology altogether rather than independently assessing and choosing each choice dimension. Ignoring such correlation between different choice dimensions might result in biased model estimation. The accommodation of multiple choice dimensions within a joint modeling framework put forward newer challenges related to the complexity associated with such estimation procedures.

Besides, a large number of the existing studies modeled vehicle type choices using cross-sectional data which captures a single episode of vehicle type choice (Bhat et al., 2009; Bhat & Sen, 2006; Spissu et al., 2009). However, households might experience multiple occasions of vehicle type choices during their lifetime which are correlated. Very few studies addressed such a correlated sequence of vehicle type choices in the same household by taking a longitudinal or panel-based modeling approach. Among them, Khan & Habib (2021) developed panel-based models to investigate vehicle transaction decisions and vehicle body type preferences to address the correlation between choices in different temporal points in the same household. Similarly, Nazari et al. (2018) developed a longitudinal fuel type choice model to investigate the adoption of hybrid and electric vehicles in California. Hence, the study contributes to the existing literature by developing a panel-based multi-dimensional vehicle type choice model to account for the repeated vehicle choice scenarios within a household.

DATA

The primary data for this study comes from the retrospective Travel Technology and Mobility Survey (TTMS) conducted in the Okanagan region of British Columbia in 2019. The study area includes five cities in Okanagan– Kelowna, West Kelowna, Vernon, Lake Country, and Peachland. TTMS collected historical information at the household level which includes vehicle ownership records, residential and employment history, life-cycle events, and attitudinal statements regarding travel modes and lifestyle. The vehicle ownership component of the survey collected information regarding both currently and previously owned vehicles by the households up to ten most recent vehicles. In addition, the make, model year, model, trim level, fuel type, purchase and disposal year, purchase price, and types of technology features available were collected for each of the vehicles. Utilizing this information, the vehicle type choice alternatives are formed as follows:

Vehicle body type:

1. Subcompact (e.g., Honda Fit, Toyota Yaris, Toyota Echo, Mini Cooper, etc.)
2. Compact (e.g., Toyota Corolla, Honda Civic, Hyundai Accent, Mazda 3, etc.)
3. Midsize/large car (e.g., Honda Accord, Toyota Camry, Chevrolet Impala, Mazda 6, Hyundai Sonata, Ford Fusion, etc.)
4. SUV (e.g., Acura MDX, Honda CR-V, Toyota RAV4, Ford Escape, BMW X5, etc.)
5. Van/truck (e.g., Honda Ridgeline, RAM 1500, Ford F-150, Toyota Sienna, Toyota Venza, Honda Odyssey, Dodge Caravan, etc.)

Vehicle vintage type:

1. New (not older than 1 year)
2. Used (2-5 years old)
3. Old (more than 5 years old)

Vehicle fuel type:

1. Gasoline
2. Diesel
3. Alternative fuel vehicles (AFVs) (includes hybrid and electric vehicles)

Vehicle technology type:

1. Availability of advanced technologies – this includes parking assist, autonomous emergency stop, lane-keep assist, and blind spot detection
2. Not available

The residential history component includes retrospective information on residential location, dwelling and tenure types, income, household composition, and technology ownership (e.g., number of smartphones, computers, google home, etc.), among others. This information was collected up to the three most recent residences for each household.

This study includes the households with multiple vehicle transaction events in their lifetime in the sample which enables testing the effect of both current and historical vehicle fleet characteristics. The sample used in this study comprises 1770 vehicles owned by 809 households. Table 1 represents the distribution of different vehicle type alternatives across different choice dimensions. The distribution for larger vehicles such as SUVs and vans/trucks was found to be 25.20% and 21.47% respectively, which are higher than that of smaller cars. Among the smaller vehicles, the share of compact (19.10%) vehicles were found to be a little higher than the subcompact (15.64 %) and midsize/ large (18.59%) cars. A larger percentage of households owned old (41.13%) and new (37.12%) cars compared to used ones. In the case of fuel types, the majority of the vehicles owned were traditional gasoline vehicles (94.86%), as expected, whereas a smaller proportion of vehicles were found to be diesel-powered and AFVs. Finally, 13.45% of the vehicles were found to be equipped with advanced technology features.

The study also utilizes some secondary data sources. For example, the location of different destinations such as restaurants, shopping centers, schools, bus stops, etc. was collected from the enhanced point of interest (EPOI) dataset. The neighborhood characteristics such as population density, dwelling density, percentage of different dwelling types, etc. were extracted from Census Canada. Furthermore, land use-related information such as the area of residential, commercial, and others was derived utilizing the open data platform of the Okanagan region.

TABLE 1 Distribution of Different Vehicle Types

Type	Percentage
Body Type	
Subcompact	15.64%
Compact	19.1%
Midsize/Large	18.59%
SUV	25.2%
Van/Truck	21.47%
Vintage Type	
New	37.12%
Used	21.75%
Old	41.13%
Fuel Type	
Gasoline	94.86%
Diesel	3.39%
AFV	1.75%
Technology Type	
Advanced Technology Available	13.45%
Not Available	86.55%

METHODOLOGY

A panel-based multi-dimensional probit modeling technique is adopted in this study to investigate vehicle type choice decisions. Four dimensions of vehicle types are considered in the model, among which vehicle body type, vintage, and fuel type are nominal variables, and the availability of advanced technology in the vehicle is a binary choice variable. The model accounts for the unobserved error correlation across different alternatives of different choice dimensions. The formulation of the multi-dimensional vehicle type choice model is based on the random utility-based discrete choice modeling technique. The utility of a household choosing a particular type of vehicle during t^{th} (t = 1, 2, …, T) choice occasion is represented as below:

$$U_{ki_kt} = \beta_k' x_{ki_kt} + \varepsilon_{ki_kt} \tag{1}$$

Here,

k = index used to denote each choice dimension; k = 1, 2, …, K ($K = 4$)
i_k = index used to denote the alternatives of k^{th} choice dimension; i_k = 1, 2, …, I_k
x_{ki_kt} = vector of explanatory variables
β_k' = vector of coefficients corresponding to the explanatory variables
ε_{ki_kt} = the unobserved error term assumed to be normally distributed

The unobserved error term ε_{ki_kt} in equation (1) is assumed to be independent and identically distributed over the households and choice occasions. However, it may have a covariance structure that reveals the dependency over the alternatives within and across different vehicle type dimensions. Let a household choose an alternative m_k for the k^{th} choice dimension during the choice occasion t. The utility-based choice theory implies that the difference in utility $\widetilde{U}_{ki_km_kt} = U_{ki_kt} - U_{km_kt}$, is negative given that $i_k \neq m_k$. Now, equation (1) can be written in terms of utility differences as $\widetilde{U}_{ki_km_kt} = \beta_k' z_{ki_km_kt} + \tilde{\varepsilon}_{ki_km_kt}$, where $z_{ki_km_kt} = x_{ki_kt} - x_{km_kt}$ and $\tilde{\varepsilon}_{ki_km_kt} = \varepsilon_{ki_kt} - \varepsilon_{km_kt}$. The vector of utility differences for the k^{th} choice dimension at choice occasion t is $\widetilde{U}_{kt} = \left[\left(\widetilde{U}_{k1m_kt}, \widetilde{U}_{k2m_kt}, \ldots, \widetilde{U}_{kIm_kt}\right)'\right]$, which has a $(I_k - 1)$ vector of parameters B_{kt}(=($\beta_k' z_{k1m_kt}$, $\beta_k' z_{k2m_kt}$, ..., $\beta_k' z_{kI_km_kt}$)), and covariance matrix Ψ_{kt}. So, the vector of utility differences can be written as follows:

$$\widetilde{U}_{kt} \sim MVN_{(I_k-1)}(B_{kt}, \Psi_{kt}) \tag{2}$$

where, $MVN_{(I_k-1)}$ is the $(I_k - 1)$ dimensional multivariate normal cumulative distribution. The covariance matrix Ψ_{kt} can be derived from the covariance matrix (Ω_k) of the vertically stacked vector of errors for k^{th} choice dimension $\varepsilon_{kt}\left(=\left[\left(\varepsilon_{k1t},\varepsilon_{k2t},\dots,\varepsilon_{kI_kt}\right)'\right]\right)$ by introducing a $(I_k-1)*\ I_k$ matrix D_k, which is an identity matrix of I_k-1 dimension with an additional column of -1 added in the m_k th column. The expression of the covariance matrix then becomes as follows (Train, 2003):

$$\Psi_{kt}=\ \mathrm{D}_k\Omega_k D_k' \tag{3}$$

Now, considering K number of choice dimensions at t^{th} choice occasion, the vertically stacked vector of utility differences $\widetilde{U}_t$ $(=\left[\left(\widetilde{U}_{1t},\widetilde{U}_{2t},\dots,\widetilde{U}_{Kt}\right)'\right])$ takes the following form:

$$\widetilde{U}_t\sim MVN_{\breve{K}}\left(B_t,\breve{\Psi}_t\right) \tag{4}$$

where, $\breve{K}=\sum_{k=1}^{K}(I_k-1)$ and $MVN_{\breve{K}}$ is the $\breve{K}$ dimensional multivariate normal cumulative distribution, B_t $(=(B_{1t},B_{2t},\dots,B_{Kt})')$ is the vector of parameters, and covariance $\breve{\Psi}_t$. The covariance matrix $\breve{\Psi}_t$ takes the following form:

$$\breve{\Psi}_t=\begin{bmatrix}\Psi_1 & \Psi_{12} & \cdot & \cdot & \cdot & \Psi_{1\breve{K}}\\ \Psi_{21} & \Psi_{22} & \cdot & \cdot & \cdot & \Psi_{2\breve{K}}\\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot\\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot\\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot\\ \Psi_{\breve{K}1} & \Psi_{\breve{K}2} & \cdot & \cdot & \cdot & \Psi_{\breve{K}}\end{bmatrix} \tag{5}$$

The off-diagonal elements of $\breve{\Psi}_t$ reveal the unobserved dependencies among the utility differences in relation to the chosen alternative for each choice dimension, thus capturing the unobserved correlation among different vehicle type choices (Paleti, 2012). The likelihood contribution of each household can be written as:

$$L\left(B,\breve{\Psi}\right)=\ \Phi_{\breve{K}*T}\left(-B,\breve{\Psi}\right) \tag{6}$$

where, $\Phi_{\breve{K}*T}$ is a $\breve{K}*T$ dimensional multivariate cumulative normal distribution function. The maximization of the likelihood function using the traditional simulation approach is computationally very expensive and the accuracy of the estimation is often compromised, especially because the complexity of the estimation of likelihood arises with the increase in the choice dimensions. Therefore, the maximum approximate composite marginal likelihood (MACML) approach is utilized here which involves a simulation-free and computationally efficient likelihood estimation. The following pairwise composite marginal likelihood (CML) function is formed for the joint pairwise probability of chosen vehicle types for a household:

$$L_{CML}=\prod_{t=1}^{T}\prod_{k=1}^{K-1}\prod_{l=k+1}^{K}P(\,h_{i_kt}=m_{kt},h_{i_lt}=m_{lt}) \tag{7}$$

In equation (7) h_{i_kt} denotes the vehicle type chosen for k^{th} choice dimension by a household at choice occasion t. Each of the pairwise probability expressions in equation (7) is of $\breve{K}_{kl}$ dimensions where $\breve{K}_{kl}=I_k+I_l-2$. Although such a pairwise approach substantially improves computational efficiency, it becomes computationally inefficient with the increase in dimensionality. Specifically, in the case of multiple nominal variables combined with repeated choice occasions the dimension of $\breve{K}_{kk'}$ is significantly high. However, pairwise probability with such high dimensions can easily be computed using the MACML method. MACML combines the CML approach with the analytical approximation of multivariate cumulative normal distribution function, leading to the computation of only univariate and bivariate cumulative normals (Bhat, 2011).

EXPLANATORY VARIABLES

A wide variety of variables were tested in the model. The distribution of the variables retained in the final model is presented in **Table 2**. The variables are thematically categorized as historical exposure to technology, historical exposure to vehicles, mobility tools, built-environment variables, and socio-demographic characteristics. Historical exposure to technology represents households' prior exposure to technology in different domains of life such as technologies used in daily life (e.g., ownership of smartphones, laptops, and google home) and technologies available in the vehicle fleet. In the case of historical exposure to vehicles, the study tested the effect of households' vehicle fleet composition in the current fleet in terms of body, vintage, and fuel type. The temporal sequence of each vehicle transaction was available in the data which was used to determine the vehicle fleet composition for each household during the purchase of each of their vehicles.

TABLE 2 Summary Statistics of the Variables Retained in the Final Model

Variable	Description	Mean or %	Standard Deviation
Historical exposure to technology			
Laptop per adult	Number of laptops per adult (age ≥ 18) in the household	1.72	1.08
Smartphone per adult	Number of smartphones per adult (age ≥ 18) in the household	1.91	0.97
Historically owned AFVs vehicle	Owned AFVs both currently and previously	1.13%	-
Historically owned advanced vehicle technology	Owned advanced technology features in the current and previously owned vehicle	4.41%	-
Historical exposure to vehicles			
Currently own subcompact	Currently own a subcompact car in the household vehicle fleet	37.01%	-
Currently own compact	Currently own a compact car in the household vehicle fleet	32.26%	-
Currently own midsize/large	Currently own a midsize/large car in the household vehicle fleet	40.85%	-
Currently own SUV	Currently own an SUV in the household vehicle fleet	44.46%	-
Currently own van/truck	Currently own a van/truck in the household vehicle fleet	40.06%	-
Currently own new vehicle	Currently own a new vehicle in the household vehicle fleet	45.76%	-
Currently own used vehicle	Currently own a used vehicle in the household vehicle fleet	38.42%	-
Currently own old vehicle	Currently own an old vehicle in the household vehicle fleet	53.22%	-
Currently own gasoline vehicle	Currently own a gasoline-powered vehicle in the household vehicle fleet	94.35%	-
Currently own AFV vehicle	Currently own an AFV in the household vehicle fleet	3.33%	-
Mobility tools			
No. of vehicles	Number of vehicles in the household	2.04	1
Bike	Owns bike in the household	73.90%	-
Transit pass	Owns transit pass in the household	19.21%	-
Built-environment characteristics			
Land use index	Land use index (value ranges from 0 to1 where the higher the index value the higher land use mix diversity in the residential area)	0.62	0.15
% of residential area	Percentage of residential area within 1-km radius of the residence	0.54	0.14
Commute distance	Distance from residence to work/school (in km)	9.92	7.13
Distance to eating/drinking place	Distance to the nearest eating/drinking places from the residence (in km)	1.28	0.98
Distance to the nearest school	Distance to the nearest education centers from the residence (in km)	1.07	0.85
Socio-demographics			
Income ≤ 50000	Annual household income ≤ $50000	41.64%	-
Income 50000-79999	Annual household income $50000-$79999	18.81%	-
Income 80000-99999	Annual household income $80000-$99999	7.34%	-
Income 100000-149999	Annual household income $100000-$149999	15.99%	-
Income≥ 150000	Annual household income ≥ $150000	16.21%	-
Average age of adults	Average age of the adults (age ≥ 18) in the household	38.36	10.95
Presence of children: no	No children in the household	56.84%	-
No. of children	Number of children in the household	1.62	1.27
No. of adults	Number of adults (age ≥ 18) in the household	1.41	0.74
Owned house	Lives in an owned house	58.31%	-
Dwelling type: single-detached	Lives in a single-detached house	57.23%	-
Dwelling type: semi-detached	Lives in a semi-detached house	4.86%	-
Dwelling type: townhouse	Lives in a townhouse	6.55%	-
Dwelling type: apartment	Lives in an apartment	8.70%	-

The mobility tool variables include the number of vehicles and ownership of bikes and transit passes in the households. The built-environment attributes of the residence include commute distance, distance to the nearest education centers and eating/ drinking places, percentage of the different land use areas, and the land use mix diversity index. The land use-related variables are derived within a 1-km radius of the residence and are categorized as residential, commercial, and other land use areas. Utilizing the land use areas, the land use index variable is generated for each residential location according to Bhat & Gossen (2004). The value of the land use index ranges from 0 to 1 and a higher value of the index indicates a higher land use mix diversity where 1 represents a perfectly heterogenous land use and 0 represents a perfectly homogenous land use. Lastly, socio-demographic characteristics include household income, number of adults (age $\geq$ 18) and children in the households, the average age of the adults, home ownership, and dwelling types, among others. Due to the availability of historical data, mobility tools, built-environment and socio-demographic variables varied over the lifetime of the household based on the timing of the vehicle purchase.

RESULTS AND DISCUSSION

The log likelihood value of the final model accounting for the error correlation is -2641.87 which is higher than that of the model without any error correlation (-2682.74)- indicating a better model fit for the joint model. The likelihood ratio test is performed to further compare the goodness-of-fit between these two models. The likelihood ratio is found to be 81.74 for 6 degrees of freedom which is significantly higher than the critical chi-squared value (12.59) at the 95% confidence interval. Therefore, the joint model capturing unobserved correlation provides a better model fit and is considered the final model. The parameter estimation results of each vehicle type component are discussed in the next sections of the paper.

Model Results for Advanced Vehicle Technology

The parameter estimation results (**Table 3**) suggest that exposure to technology in different life domains such as in daily life and in vehicles has a significant effect on the preference for vehicles with advanced technology. For example, the likelihood of preferring such vehicles increases with the increase in the number of smartphones and laptops per person in the household. These households are likely to be more technology-dependent in their daily lives which may have translated to the decisions of vehicle type. As a result, they might be more comfortable with advanced features in the vehicle. The model results further reveal that there is a historical aspect of technology ownership in vehicles. For example,

TABLE 3 Parameter Estimation Results of the Technology Type Model

Variables	**Coeff.**	**t-stat.**
Constant	-1.75	-17.30
Historical exposure to technology		
No. of smartphones per person	0.24	1.39
No. of laptops per person	0.06	1.62
Historically own advanced technology in vehicles	0.81	9.21
Historically own AFV	1.56	3.42
Socio-demographics		
Income 80000-99999	0.18	1.39
Income $\geq$ 150000	1.15	15.99
Average age of adults in the household	-1.18	-5.37
Dwelling type: owned & single-detached	0.56	7.00
Rented house	-0.17	-1.54
Note: Coeff. = co-efficient; stat. = statistic		

households that historically owned advanced technology in vehicles and AFVs are found to be more inclined towards owning vehicles with advanced technology. This result might imply that the adoption of newer forms of technology is influenced by familiarity and prior experience with similar technology (Venkatesh et al., 2003). In other words, individuals are more likely to adopt a newer form of technology if they have previous exposure to technology as their prior experience will make them more comfortable and efficient in using such technology.

The model results also suggest that high-income households (annual household income ≥ \$150000) have a higher likelihood of owning vehicles with advanced technology. High-income households are financially in a better position to afford these vehicles because of the high purchase price. The likelihood of owning these vehicles decreases with the increase in the average age of the adults in the household. It is expected that younger individuals are more tech-savvy and tend to adapt to newer forms of technology. On the other hand, older individuals are likely to be less attracted to newer forms of technology and therefore might show lower interest in owning advanced vehicle technology.

Model Results for Vehicle Fuel Type

Table 4 shows the parameter estimation results of the fuel type model. Current AFV owners reveal a lower interest in owning gasoline vehicles. Similarly, having a gasoline vehicle in the current fleet has a negative association with the preference for AFVs. These results may represent the existence of the inertia effect, as households choose the same vehicle even when another alternative could be rationally more attractive. Among the mobility tools, ownership of vehicles, bikes, and transit passes are found to be significant factors affecting fuel type choices. Households having a higher number of vehicles per adult are less likely to prefer gasoline vehicles. Owning a higher number of vehicles might be associated with higher fuel consumption leading to a higher carbon footprint. Such households might grow increased awareness due to owning more vehicles and might seek alternative and cleaner fuel options and thus reducing interest in gasoline-powered vehicles. The model results suggest that ownership of bikes and transit passes are positively associated with the preference for AFVs. Bike and transit pass owners might be more concerned about the environment and prefer more sustainable travel modes to reduce their environmental footprint. The results also reveal significant effects of built-environment attributes on the preference for vehicle fuel type. For instance, households living farther from destinations such as schools and eating/drinking places have a higher likelihood of owning AFVs. A similar relationship is observed for commute distances where households commuting higher distances are likely to own AFVs. The savings in fuel costs and environmental benefits might be the influential factors behind such choices.

In the case of socio-demographic attributes, the findings suggest that lower-income (annual household income ≤ \$50000) households are more inclined towards conventional gasoline vehicles. On the other hand, high-income households whose annual income is \$150000 or more have a higher likelihood of owning AFVs. Very similar findings were suggested by some of the earlier studies such as Nazari et al. (2018) and Nazari, Mohammadian, et al. (2019). High-income households are likely to have more financial leverage to afford AFVs which are generally more expensive than conventional gasoline and diesel. In the case of middle-income households (annual household income \$50000-\$79999), they are found to be inclined towards both gasoline and AFVs. This result provides an interesting insight. For them, the initial cost of purchasing AFVs might be challenging but the overall savings on fuel costs and environmental benefits might encourage them to purchase AFVs. Furthermore, the model results suggest that with the increase in the average age of adults in the households, the preference for owning AFVs decreases significantly. Younger individuals are more likely to be tech-savvy and have a higher likelihood of adopting emerging vehicular alternatives such as the AFVs whereas older individuals might not be comfortable with such vehicular options and might prefer the trusted technologies of gasoline vehicles (Shin et al., 2015).

TABLE 4 Parameter Estimation Results of Vehicle Fuel Type Model

Variables	Gasoline		AFV	
	Coeff.	**t-stat.**	**Coeff.**	**t-stat.**
Constant	0.75	3.71	0.06	0.16
Historical exposure to vehicles				
Currently own alternate fuel vehicle (AFV)	-1.6	-11.74	-	-
Currently own gas vehicle	-	-	-1.76	-10
Mobility tools				
Vehicle per adult	-1.19	-5.93	-	-
Own bike	-	-	0.8	2.88
Own transit pass	-	-	0.32	1.31
Built-environment characteristics				
Commute distance	-	-	1.17	2.34
Distance to the nearest school	-	-	1.26	2.13
Distance to the nearest eating/drinking place	-0.64	-1.89	1.46	2.04
Socio-demographics				
Income ≤ 50000	1.5	8.06	-	-
Income 50000-79999	3.83	1.77	2.45	1.13
Income ≥ 150000	-	-	0.77	2.84
Average age of adults in the household	-	-	-4.18	-9.93
Owned house	0.68	4.88	-	-
Dwelling type: single-detached	1.53	8.76	-	-

Note: Base Alternative = diesel; Coeff. = co-efficient; stat. = statistic; “-” = not significant

Model Results for Vehicle Body Type

The parameter estimation results of the vehicle body type choice model are presented in **Table 5**. Existing vehicle fleet compositions are found to be significant determinants of households’ vehicle body type choices. The model results indicate that households are less likely to prefer smaller vehicles if they already own larger vehicles. For example, households owning SUVs and vans/trucks in the current fleet are less likely to prefer subcompact and midsize/large cars respectively. The comfort and convenience provided by the larger vehicles in terms of cabin and cargo space might be a significant factor for such a choice pattern. The number of vehicles currently owned by the household is found to have a significant effect on vehicle body type preference. For instance, the likelihood of owning midsize/ large cars and SUVs increases with the increase in the number of vehicles in the household. Such preferences might be induced by the special travel needs of the households (Potoglou, 2008). For example, multiple-vehicle households might prefer to own a comparatively larger vehicle that offers more cabin and cargo space and utilize it for recreational and shopping trips. Interestingly, households having bikes are found to be more inclined towards owning compact cars whereas they are less likely to own SUVs. The result differs from the finding of Cao et al. (2006) which indicates a positive relationship between owning a bike and SUVs due to the higher carrying capacity. However, bike owners might be more environment-concerned which might lead them to prefer more energy-efficient vehicles such as compact cars rather than choosing SUVs (Potoglou, 2008). They can also attach external bike carriers to their compact cars to carry the bikes. Furthermore, the land use mix diversity and the neighborhood characteristics of the residence have significant effects on households’ vehicle body type preferences. For example, people living in lower land use diverse areas are found to be more interested in owning larger cars which is consistent with the findings of Chen et al. (2021).

The model results also suggest that lower-income households (annual household income ≤ $50000) are more likely to prefer smaller vehicles such as compact and subcompact cars. The middle-income households (income $50000-$79999) show very similar behavior as lower-income households. On the other hand, relatively higher-income households (e.g., income $80000-$99999) are found to be more interested in larger vehicles such as midsize/large and van/truck. These results are consistent with the findings of the existing studies such as Chen et al. (Chen et al., 2021) and Khan and Habib (Khan & Habib, 2021). As the purchase price and operating and maintenance costs of the larger vehicles are often higher than the smaller compact cars, high-income households are more likely to afford such vehicles.

TABLE 5 Parameter Estimation Results of Vehicle Body Type Choice

Variable	Subcompact		Compact		Midsize/Large		SUV	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Constant	-0.75	-2.83	-2.68	-9.53	-0.79	-2.7	-1.29	-4.85
Historical exposure to vehicles								
Currently own subcompact	1.63	11.55	-	-	-	-	-	-
Currently own compact	-	-	2.41	11.99	-	-	-	-
Currently own midsize/large	-	-	-	-	2.21	15.01	-	-
Currently own SUV	-0.6	-3.81	-	-	-	-	2.5	8.64
Currently own van/truck	-	-	-	-	-1.34	-13.33	-1.15	-12.98
Mobility tools								
No. of vehicles	-	-	-	-	0.29	2.6	0.4	2.82
Bike	-	-	0.74	3.15	-	-	-0.07	-1.21
Built-environment characteristics								
Land use index	-	-	-	-	-0.55	-1.86	-0.55	-2.13
% of residential area	-3.17	-5.45	-	-	-	-	-	-
Socio-demographics								
Income ≤ 50000	0.9	5.36	0.32	3.33	-	-	-	-
Income 50000-79999	0.85	5.2	-	-	-	-	-	-
Income 80000-99999	-	-	0.29	0.95	0.72	2.63	0.26	2.25
Presence of children: no	0.13	1.16	0.44	2.36	-	-	-	-
No. of children	-	-	-	-	-	-	0.62	3.8
No. of adults	2.24	8.84	-	-	-	-	-	-
Rented house	0.24	2.96	0.44	1.84	0.22	2.79	-	-
Dwelling type: semi-detached	-	-	-1.42	-5.89	-0.99	-6.55	0.33	2.21
Dwelling type: apartment	-	-	1.01	4.71	0.32	2.29	-	-

Note: Base alternative = van/truck; Coeff. = co-efficient; stat. = statistic; “-” = not significant

The presence of children in the household is an important factor that influences the vehicle body type choice which has been also identified by past studies (Bhat & Sen, 2006; Potoglou, 2008; Vyas et al., 2012). The number of children in the household is found to have a positive effect on the choice for SUVs which indicates the likelihood of owning SUVs will increase with the increase in the number of children. On the other hand, households without children are more likely to prefer smaller vehicles such as subcompact and compact cars. The presence of children might induce the need for additional passenger and cargo space in the vehicle for carrying children and child-care equipment (e.g., baby strollers and car seats) and therefore, households might have a higher preference for larger vehicles (Vyas et al., 2012).

Model Results for Vehicle Vintage

The results of the vehicle vintage type model are presented in **Table 6**. The vintage of the currently owned vehicles is found to have a significant effect. For example, owning old vehicles in the fleet is found to be negatively associated with both new and used vehicle purchases. Purchasing a new or used vehicle may be less feasible for owners of older vehicles due to their potentially lower financial solvency. On the other hand, owning used vehicles is found to have a positive effect on both new and used vehicle purchases. Similarly, currently owning a new vehicle has a positive association with the preference for a new vehicle. These findings reveal households' interest in newer vehicles. For instance, new and used vehicle owners might be more interested in those vehicle features and likely to upgrade their vehicle fleet by purchasing vehicles of the most recent models and trims. Interestingly, with the increase in the number of vehicles in the household, the likelihood of owning new vehicles is likely to decrease whereas an opposite relationship is observed in the case of owning used vehicles. The higher cost of purchasing newer vehicles than used vehicles might be one of the possible reasons behind such choices. As the number of vehicles in the household increases, it becomes increasingly difficult for households to afford to buy newer vehicles. As a result, purchasing used vehicles with a lower price becomes a more affordable option for them.

TABLE 6 Parameter Estimation Results of Vehicle Vintage Choice

Variables	**New**		**Used**	
	Coeff.	**t-stat.**	**Coeff.**	**t-stat.**
Constant	-0.47	-2.93	-1.45	-5.38
Historical exposure to vehicles				
Currently own new	3.25	22.95	-	-
Currently own used	0.23	2.2	0.09	0.77
Currently own old	-3.16	-17.33	-0.59	-7.86
Mobility tools				
No. of vehicles	-0.44	-4.11	1.57	14.74
Socio-demographics				
Income 80000-99999	-	-	0.57	6.00
Income ≥ 100000	0.28	2.33	-	-
Average age of adults in the household	1.37	5.36	-1.73	-11.58
Owned house	-	-	0.37	6.23
Dwelling type: owned & single-detached	0.24	2.21	-	-
Dwelling type: single-detached	-	-	0.09	1.77
Dwelling type: townhouse	-1.13	-2.06	-0.49	-3.63
Dwelling type: apartment	-	-	-0.10	-0.95

Note: Base alternative: old; Coeff. = co-efficient; stat. = statistic; "-" = not significant

In the case of socio-demographic characteristics, the findings suggest that higher-income households having annual income of $100000 or more have a higher likelihood of owning new vehicles whereas medium to high-income households ($80000-$99999) are likely to own used vehicles. Interestingly, with the increase in the average age of the adults in the household, the likelihood of owning new vehicles increases. On the other hand, an opposite relationship is found in the case of owning used vehicles. Although these findings differ from the findings of Mohammadian & Miller (2003), our results might indicate that households gain more financial stability as family members age and are thus able to afford new vehicles later in the life stage.

Error Correlation among Vehicle Type Dimensions and Alternatives

Table 7 represents the covariance matrix of utility differentials of the vehicle type choices with respect to the base alternative for each nominal variable. A positive and significant covariance (0.46) is found between AFVs and vehicles with advanced technology. This indicates that if an unobserved factor motivates a household to purchase a vehicle with advanced technology, the same factor might also positively influence them to purchase an AFV. This result might represent someone who prioritizes environmental concerns and safety might choose AFVs as well as choose to have advanced technology in their vehicle. A negative and significant correlation (-0.54) is found between the AFVs and SUVs. The result indicates that common unobserved factors have opposite effects on the choices for AFVs and

SUVs. For example, if an individual possesses an environmental-concerned attitude (which is an unobserved factor) might increase the likelihood of owning AFVs while decreasing the likelihood of owning larger vehicles like SUVs which are less fuel efficient and environment friendly – for example, from a life cycle perspective. Furthermore, a significant positive correlation is found between new vehicles and vehicles with advanced technology. Such a relationship might represent the tech-savvy individuals who are more likely to be inclined towards the advanced technology features of the vehicles and likely to keep their vehicle fleet up-to-date by owning vehicles of newer models and trim levels.

TABLE 7 Covariance Matrix of Vehicle Type Choices

	Sub-compact	**Compact**	**Midsize/ Large**	**SUV**	**New**	**Used**	**Gasoline**	**AFV**	**Advanced Technology**
Sub-compact	1								
Compact	0.5	1							
Midsize/Large	0.5	0.5	1						
SUV	0.5	0.5	0.5	1					
New	0	0.12 (1.42)	0	0	1				
Used	0	0	0	0	0.5	1			
Gasoline	0	0	0	0	0	0	1		
AFV	0	0	0	-0.54 (-2.42)	0.54 (1.33)	0	0.5	1	
Advanced Technology	0	0	0.27 (2.45)	0	0.64 (4.39)	0	0	0.46 (2.26)	1

Note: *t*-statistics are provided in parentheses. Covariance without any *t*-statistics is fixed to the shown values.

CONCLUSION

The study develops a joint model to investigate households' vehicle type choices in the following four dimensions: body type, vintage type, fuel type, and technology type. Specifically, a panel-based multi-dimensional probit modeling framework is developed to capture the unobserved error correlations among different vehicle type choices. The joint model also reveals significant correlations across different vehicle type choice categories. For instance, the common unobserved factors are found to have a similar effect on the choice of advanced vehicle technology and AFVs. On the other hand, a negative correlation was found between the choices for AFVs and SUVs. This existence of significant error correlations among different choice dimensions confirms the need for such joint modeling procedures. The model results provide important behavioral insights by revealing the key factors contributing to households' vehicle choice decisions such as exposure to technology. Historical exposure to technology and vehicles, mobility tools, built-environment attributes, and sociodemographic characteristics are found to be the key determinants of vehicle choices. In the case of owning advanced vehicle technology, households with higher exposure to technology in daily life and in the vehicle show a higher likelihood. Additionally, historically AFV owners have an inclination towards owning advanced vehicle technology. The model results confirm the inertia effects of the current vehicle fleet on the preference for vintage and fuel types. For instance, current AFV owners are less likely to own gasoline vehicles.

In the case of advanced vehicle technologies, older adults are found to be less inclined to have such technologies in their vehicles. Although they could tremendously benefit and have a much safer driving experience using these technologies such as parking assist, this result could indicate their hesitance towards using newer technologies. In fact, the testing of technology-related variables in this study confirms that households who are exposed to advanced technologies in their daily life and in their vehicles are more inclined towards advanced vehicle technologies. This indicates a need for more targeted programming, marketing, and training for older adults to use such technologies. This would further pave the path to transition into autonomous vehicle technology and leverage tremendous benefits from it. Although results suggest that higher-income groups are the target population for advanced vehicle technologies and AFVs, one of the main barriers for comparatively lower-income groups to access these environment-friendly and safer vehicles could be the price points. For example, medium-income households showed positive relationships to both gasoline and AFVs; however, low-income groups showed a higher likelihood towards gasoline vehicles. This indicates a need for targeted rebates such as text incentives and/or direct incentives based on income, which could give equitable access to households from diverse income groups to these newer technology vehicles. Notably, transit pass ownership and households with bikes showed an inclination towards AFVs. This indicates careful monitoring of whether environment-friendly people are shifting their travel mode such as from transit to cars due to the availability of AFVs. In such cases, monitoring of the early adopters and clear messaging, campaigning, and marketing are required to distribute the benefits and challenges associated with AFVs such as reduction emissions, life-cycle environmental impacts, and limited impact on reducing congestion.

The findings of the study might be helpful for land use-related policymaking and targeted marketing to promote ownership of more sustainable, compact, and fuel-efficient vehicles. For example, individuals commuting longer distances and living further from key destinations (e.g., schools and eating/drinking places) are likely to own AFVs. Furthermore, individuals living in lower land use mix areas are more inclined towards owning larger vehicles. These results inform the policymakers about planning and designing land use and transportation system to influence households' vehicle type choices in a way to mitigate fuel consumption and emissions.

Nevertheless, the study provides important behavioral insights and direction for policy planning. The vehicle type choice model developed in this study will be included within an integrated urban model, which is currently under development. The model is expected to improve the prediction accuracy of owned vehicle types, which will consequently improve the simulation of households' energy consumption and GHG emissions under alternative transportation and land use policy scenarios. However, one of the limitations of the study is a much smaller proportion of AFVs which includes both hybrid and electric vehicles. As a result, these fuel types were aggregated for modeling which limits the study to shed light on households' preferences for these fuel types at a disaggregate level. Future research should focus on more extensive data collection to overcome this limitation. Furthermore, the modeling framework used in the study does not account for the unobserved heterogeneity that might exist among the households regarding their preferences for different vehicle types. One of the immediate future research could be to develop a more advanced modeling framework to capture such heterogeneity.

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