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Evaluating the Impacts of Autonomous Electric Vehicles Adoption on Vehicle Miles Traveled and CO_2 Emissions

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Abstract: Autonomous electric vehicles (AEVs) can potentially revolutionize the transportation landscape, offering a safer, contact-free, easily accessible, and more eco-friendly mode of travel. Prior to the market uptake of AEVs, it is critical to understand the consumer segments that are most likely to adopt these vehicles. Beyond market adoption, it is also important to quantify the impact of AEVs on broader transportation systems and the environment, such as impacts on the annual vehicle miles traveled (VMT) and greenhouse gas (GHG) emissions. In this pilot study, using survey data, a statistical model correlating AEV adoption intention and socioeconomic and built environment attributes was estimated, and a sensitivity analysis was conducted to understand the importance of factors impacting AEV adoption. We found that the market segments range from early adopters who are wealthy, technologically savvy, and relatively young to non-adopters who are more cautious to new technologies. This is followed by a synthetic population microsimulation of market penetration for the San Francisco Bay Area. With five household vehicle replacement scenarios, we assessed the annual VMT and tailpipe carbon dioxide (CO_2) emissions change associated with vehicle replacement. It is found that adopting AEVs can potentially reduce more than 5 megatons of CO_2 yearly, which is approximately 30% of the total CO_2 emitted by internal combustion engine (ICE) cars in the region.

Keywords: autonomous electric vehicles; microsimulation; market scenarios; demand model; vehicle miles traveled; greenhouse gas emissions

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1. Introduction

Autonomous vehicles (AVs) can potentially revolutionize the transportation landscape, offering a safer, contact-free, easily accessible, and more eco-friendly mode of travel [1,2]. The intention to adopt AVs is influenced by a combination of factors, including demographic characteristics, socio-economic status, behavioral patterns, and individual attitudes. Market research has identified that younger and wealthier people with higher educational attainment are more inclined to adopt AVs [3–6]. Behavioral factors, such as travel mode preferences, also play a significant role in the intention to adopt AVs. Studies have found that individuals who frequently use public transit, ridesharing, or other modes of transportation tend to have a more positive view of AVs [7–9]. To better understand the latent attitudinal variables, theories like the Technology Acceptance Model (TAM) [10] and the Theory of Planned Behavior (TPB) [11] are widely applied. Research has shown that factors such as perceived usefulness [8], environmental awareness [12], and technology savviness [9,13] are key factors of AV adoption. Consumers who are more open to new technologies are generally more likely to embrace AVs, suggesting that personal attitudes toward innovation play a critical role in the adoption decision [9].

The impact of adopting AVs on transportation systems has become a prominent research topic, given its potential to significantly reshape mobility, vehicle ownership, travel demand, road capacity, and infrastructure needs [14,15]. Studies have found that high penetration of AVs could lead to a substantial increase in road capacity through platooning [16] and a reduction in parking demand [17]. The literature on the potential effects of AV adoption (or ownership) on travel demand remains inconclusive [15]. The introduction of autonomous technology is expected to increase vehicle utilization rates, particularly through on-demand services such as autonomous ride-hailing and car-sharing [9]. These services could reduce the number of privately owned vehicles on the road, potentially alleviating congestion [18,19]. However, some studies suggest that the convenience and flexibility offered by AVs may increase overall travel demand, particularly in urban areas, as consumers may opt for more spontaneous trips. Additionally, autonomous driving could encourage long-distance travel, which may increase vehicle miles traveled (VMT) [20–22]. The overall impact on VMT remains uncertain and will depend on how AVs are integrated into existing transportation networks, as well as whether they primarily serve as shared mobility solutions or continue to be used as privately owned vehicles.

The environmental impact of AV adoption has been extensively studied. Since AVs can communicate with each other and optimize traffic flow, they have the potential to increase road capacity [23,24], reduce traffic congestion [18], and subsequently lower energy consumption and greenhouse gas (GHG) emissions [24]. Additionally, the ability of AVs to increase vehicle utilization rates in urban areas through ridesharing and reduce vehicle ownership could further reduce energy use and carbon dioxide (CO_2) emissions [25]. Unlike internal combustion engine (ICE) vehicles, EVs produce zero tailpipe emissions, directly reducing air pollution. Numerous studies have demonstrated that EVs can substantially lower CO_2 emissions, especially in regions where the electricity grid is powered by renewable or low-carbon energy sources [26]. By improving traffic efficiency, facilitating more sustainable travel patterns, and integrating EVs with AVs (i.e., autonomous electric vehicles, also known as AEVs), AEVs offer a promising path toward a cleaner, more energy-efficient transportation system.

Car ownership and vehicle replacement are long-standing research topics in travel behavior and have motivated a variety of studies spanning a wide spectrum of policy questions including social exclusion [27], cultural and social assimilation [28], residential location choice and car use [29], and of course the strong relationship with fuel type choice [30]. The decision to replace traditional ICE vehicles with AEVs is influenced by a range of factors, including cost considerations and environmental motivations. Safety improvements, increased accessibility, lower per-mile ”fuel“ costs, reduced maintenance expenses, and government incentives can make AEV ownership more attractive. Additionally, the zero tailpipe emissions of AEVs appeal to environmentally conscious individuals seeking to reduce their carbon footprint and contribute to sustainability efforts. However, despite these advantages, barriers such as range anxiety, concerns over vehicle performance in extreme weather conditions, and the availability of charging infrastructure remain significant obstacles for potential AEV adopters [31]. When a household owns more than one vehicle, the decision of which vehicle to replace with an AEV is influenced by factors such as vehicle usage patterns, vehicle age, and condition [32]. Replacing an older vehicle typically offers greater environmental benefits as it can lead to a more significant reduction in GHG emissions. On the other hand, replacing a high-mileage vehicle may result in greater fuel cost savings over time, as these vehicles tend to have higher operating costs. In general, the choice of which vehicle to replace with an AEV depends on both environmental and financial considerations.

While existing studies typically use aggregate-level penetration rates to estimate the impacts of AV and/or EV adoption, few have explored individual-level adoption patterns and applied AEV replacement scenarios to assess their effects on VMT and CO_2 emissions. In this study, using the 2019 California Vehicle Survey data, an ordinal logistic model was built to understand the relationship between people’s intention to buy an AV and their socioeconomic and built environment attributes at the household level. Sensitivity analysis was conducted to understand the importance of the covariates that impact AV adoption. The results suggest that electric vehicle (EV) ownership greatly affects the intention to adopt AVs. This motivated the research to jointly study AVs and EVs together, given their significant potential to contribute to the decarbonization of the transport sector. Applying an estimated ordinal model to the synthetic population of the nine counties in the San Francisco (SF) Bay Area region, Monte Carlo simulations were generated to simulate the market share of AEVs and assess how travel-related measures such as VMT and tailpipe CO_2 emissions change at the regional level, while solely accounting for the behavioral utilization aspect. Five vehicle replacement scenarios were developed to assess AEV adoption impacts; they included replacing an AEV with (1) the highest VMT vehicle in a household, (2) the lowest VMT vehicle in a household, (3) the electric vehicle in a household, (4) the oldest vehicle (defined by vehicle age) of a household fleet, and (5) a random vehicle in the fleet. For each scenario, the simulated data were used to assess the impact on VMT and GHG emissions per replacement scenario. It was found that adopting AEVs can reduce more than 5 megatons of CO_2 yearly, which is around 30% of the total CO_2 emitted by ICE vehicles in the synthetic population. This study enhances our understanding of the important covariates that influence AEV adoption (or ownership). Further, the microsimulation approach adopted in this study quantifies the impact of AEV adoption on transportation systems and the environment. It also points to a new direction in AV and EV research that can simulate an entire region and assess the impact of the complex relationships among technology, policy design, and behavior at the most foundational level of decision making.

The structure of this paper is organized as follows. The next section introduces the survey and datasets used in this study. The third section presents the modeling methodology. The fourth section outlines the results of the model estimation. Concluding thoughts, linkage to the energy and technology literature, and directions for future research are provided in the fifth and final section.

2. Data Description

This study aims to understand people's intention to adopt (or own) AVs and to identify covariates that significantly impact AV adoption. The estimated AV adoption model is applied to the synthetic population and vehicle data for nine counties in the SF Bay area to evaluate impacts of adoption. Detailed descriptions of the two following datasets are presented in this section: (a) 2019 California Vehicle Survey; (b) Synthetic population and vehicle data of the San Francisco Bay Area region.

2.1. 2019 California Vehicle Survey Data

This research uses data from the 2019 California Vehicle Survey (CVS) [33], which was conducted periodically on residential and commercial light-duty vehicle ownership. The survey also has a subset of targeted EV users to gather insights on their charging behavior and purchase motivation. The survey included a questionnaire regarding the preference of adopting AVs, which is detailed in Section 2.1.2.

2.1.1. Household Characteristics

The 2019 CVS dataset contains a total of 4248 households, encompassing 8365 individuals (average household size, 2 persons) and 8049 vehicles (average household vehicle ownership, 2 vehicles). The descriptive statistics of the sample households are presented in Table 1. The population statistics are based on the US Census American Community Survey (ACS) 2015-2019 5-year estimates. While there are slight differences between sample and population characteristics, the socio-demographic characteristics are controlled in the modeling process, as explained later in this paper.

Table 1. Household-level descriptive statistics (N = 4248).

Variable	Category	Sample	Sample (%) (N = 4248)	Population (%) (N = 13,044,266)
Household size	1	1090	25.66	23.81
	2	1867	43.95	30.42
	3	593	13.96	16.69
	4	482	11.35	15.25
	5 or more	216	5.08	13.83
Number of children [ab]	0	3453	81.28	65.63
	1 or more	795	18.72	34.37
Householder age [b]	18 to 64	2774	65.30	76.06
	65 and over	1474	34.70	23.94
Household Income	Less than $24,999	294	6.92	16.39
	25,000 to 49,999	575	13.54	17.96
	50,000 to 99,999	1213	28.55	27.93
	100,000 to 149,999	779	18.34	16.63
	150,000 to 199,999	430	10.12	8.93
	$200,000 or more	582	13.70	12.16
	Prefer not to answer	375	8.83	-
Total Housing Units	1 (detached or attached)	3191	75.12	65.34
	2 to 4	214	5.04	7.82
	5 to 19	313	7.37	11.17
	20 or more	397	9.34	12.13
	Mobile home	104	2.45	3.43
	Boat, RV, Van, etc.	9	0.21	0.12
	Others	20	0.47	-
Number of vehicles	0	112	2.64	7.11
	1	1529	35.99	30.42
	2	1713	40.32	37.20
	3	607	14.29	16.20
	4 or more	287	6.76	9.07
Owns electric vehicle(s) (0/1)		1174	27.64	-
Has solar panels installed (0/1)		667	15.70	-
Region	Central Valley	249	5.86	9.87
	Los Angeles	1922	45.25	46.23
	San Diego	388	9.13	8.63
	San Francisco	1005	23.66	20.94
	Sacramento	343	8.07	6.82
	Rest of State	336	7.91	7.51
	I don't know	5	0.12	-
Endogenous Variable	**Response**			**Sample (%) (N = 4248)**
Non-adopters	We would wait as long as possible and try to avoid ever buying a self-driving vehicle.			46.07
Late adopters	We would eventually buy a self-driving vehicle, but only after they are in common use.			44.96
Early adopters	We would be one of the first to buy a self-driving vehicle (either as a replacement or additional household vehicle).			8.97

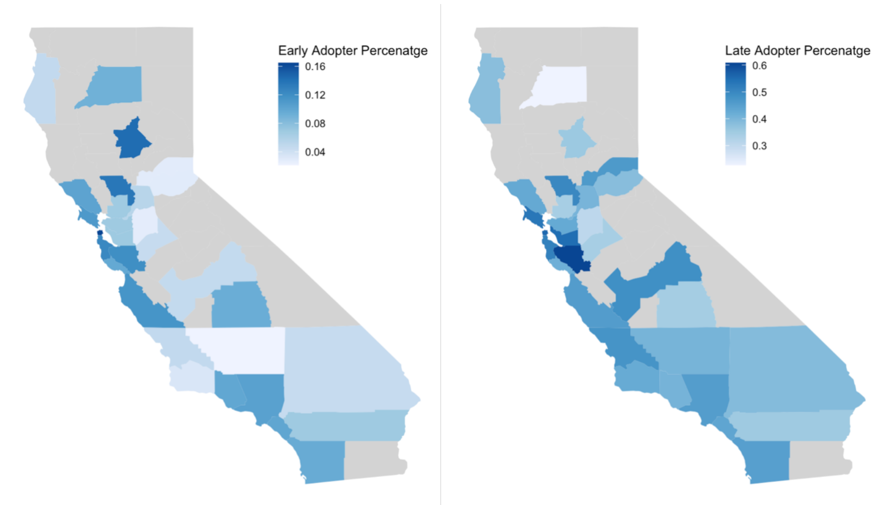
Note: (0/1) indicates binary variable. a: Children are defined differently in CVS (i.e., individuals below 16 years old) and in the ACS data (below 18 years old). b: The statistics are based on aggregated categories for comparison purposes given that the categories in CVS and ACS are not completely the same. The finer categories are used in analysis and modeling.

Some derived variables are used in the modeling process but not included in Table 1. For example, the *healthcare and social assistance* industry, one of the 20 sectors according to North American Industry Classification System (NAICS), is used as a binary indicator variable indicating whether this industry is the top 2 industry in terms of employment population in the county where the household is located. The reason is that people's travel behavior and their intentions to adopt AVs can be influenced by various types of employment. More details on the dataset can be found in Xiao and Goulias [8].

Compared to the California population, the sample households have smaller household sizes, a lower number of children, and more seniors with higher income. In terms of vehicle usage, the sample households have a lower car ownership (number of vehicles) but higher percentage of EV owners (The EVs here include hybrid electric vehicles, plug-in hybrid electric vehicles, fuel cell electric vehicles, and battery electric vehicles). The geographical distribution of the sample households is similar to the population at the regional level. The percentage of households across most categories varies by no more than 5% between the sample and the population, indicating that the sample is likely representative of the population.

2.1.2. Endogenous Variable: Intention to Adopt AVs

We use the following survey question—"Now, consider your current situation with the vehicles your household now owns (if any), and imagine that driverless vehicles have become widely available for purchase. Which of the following scenarios best describes your household?" to create the endogenous variable so that the sample is in three categories: early adopters, late adopters, and non-adopters. As shown in Table 1, early adopters account for 9% of the sample. Late adopters and non-adopters constitute 45% and 46%, respectively. Figure 1 displays the spatial distributions of (a) "early adopter" and (b) "late adopter" for California at the county level. The coastal region, including the San Francisco Bay Area, is more positive to AV adoption in general, although the majority of households are considered late adopters. In broader terms, the inclination to own an AV (late or early) among the residents of the coastal region might be attributed to area characteristics (e.g., presence of more technology companies) making them more technology savvy.



(**a**) (**b**)

Figure 1. (**a**) Early adopter and (**b**) late adopter distribution at the county level in California, USA. (Counties in gray have less than 20 observations).

2.2. Synthetic Population and Vehicle Data of the San Francisco Bay Area Region

This study uses a synthetic population and household vehicle data for the year 2017 for microsimulation. The population data are generated by a demographic model (urbanSim: https://github.com/psrc/urbansim/tree/master/urbansim/models (last accessed on 3 November 2024) implemented in urbanSim [34] by evolving the model yearly from a base year 2010 to 2017. A population synthesizer SynthPop (SynthPop: https://github.com/UDST/synthpop (last accessed on 3 November 2024) is used to create the base year population that initializes the urbanSim model. A synthetic population is the person-by-person and household-by-household representation of the population residing in a region. It uses a relatively large sample of microdata (called the seed) and clones the persons and households of the sample in a way that the resulting population matches the characteristics of the real resident population with high fidelity. The fidelity of this simulation is by using statistical criteria of fit between the synthesized persons and households in each geographic unit (e.g., the US Census block group) to the demographic characteristics provided by the

US Census. The synthetic population used here contains over 6.8 million individuals living in over 2.5 million households owning around 5 million vehicles. The households are in the nine counties of the San Francisco Bay Area region (Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma) of Northern California.

Vehicle ownership level and fleet composition associated with the individual households in the synthetic population of year 2017 are generated by a vehicle fleet mix module implemented in the vehicle transaction and technology adoption microsimulator ATLAS (Automobile and Technology Lifecycle-Based ASsignment) [35,36] as part of a larger mesoscale agent-based transportation modeling system (BEAM CORE: Behavior, Energy, Autonomy, and Mobility Comprehensive Regional Evaluator) [37]. Depending on the socioeconomic and demographic attributes of the household, ATLAS predicts the number of vehicles owned, and the body type, vintage, powertrain, tenure (own or lease), and annual mileage of each of these vehicles.

Table 2 presents the descriptive statistics of the synthetic population and household vehicles. On average, the number of vehicles owned per household is approximately two, which is consistent with our expectation. Further, the average VMT per household is 18,910 miles per year and average VMT per vehicle is computed as 9471 miles per year, consistent with the US Energy Information Administration [38]. The synthetic vehicles data was generated from the vehicle ownership and transaction model developed at Lawrence Berkeley National Laboratory; ATLAS [35] is also used in this study. Characteristics of the synthetic vehicles are displayed in Table 2. About two-thirds of the vehicle body types are passenger cars, while about one-fifth of them are sports utility vehicles (SUVs). The majority of the vehicles are ICE, and more than 90 percent of the vehicles are owned by the households. Interestingly, the dataset contains an equal proportion of vehicles aged 0–5 years and 12+ years. Overall, the synthetic dataset provides rich information to assess the implications of AEVs on VMT and GHG emissions.

Table 2. Descriptive statistics of the synthetic population and the synthetic vehicles.

Variable	Count / Median	Percent / IQR [a]
Number of households	2,530,071	-
Number of persons (avg./household)	6,849,690 (2.71)	-
Number of vehicles (avg./household)	5,051,465 (2.00)	-
Total mileages for all households	47,844,975,328	-
Average VMT per household	18,910.53	-
Average VMT per vehicle	9471.505	-
Body type		
Car	3,355,656	66.43%
SUV	1,057,989	20.94%
Pickup	368,167	7.29%
Van	269,653	5.34%
Vintage		
0∼5 years	1,794,177	35.52%
6∼11 years	1,459,110	28.88%
12+ years	1,798,178	35.60%
Annual mileage	7230	(3310, 13,067)
Fuel type [b]		
ICE	4,595,581	90.98%
Hybrid	330,318	6.54%
AEV	70,138	1.39%
PHEV	55,428	1.10%
Tenure		
Own	4,721,254	93.46%
Lease	330,211	6.54%

Note: a: IQR = interquartile range. b: ICE = Internal Combustion Engine; Hybrid = Hybrid Electric Vehicle; PHEV = Plug-in Hybrid Electric Vehicle; AEV = All-Electric Vehicle, also known as Battery Electric Vehicle (BEV).

3. Methods

This section presents an ordinal logistic model that utilizes the 2019 CVS data followed by sensitivity analysis to understand the role of exogenous attributes in differentiating early adopters from non-adopters. Then, the ordinal model is applied to the synthetic population created for the nine-counties in San Francisco Bay Area in California, using Monte Carlo simulations. In this way, the market uptake of AEVs in different scenarios of behavioral response and concomitant vehicle ownership changes can be estimated.

3.1. Ordinal Logistic Model

The outcome variable intention to adopt AVs has three ordered responses (i.e., non-adopter, late adopter, and early adopter). An ordered logistic model is used to find the correlations between people's intention to adopt AVs and their socio-economic characteristics and environmental variables.

3.2. Sensitivity Analysis

Statistical significance of a behavioral determinant is not sufficient to assess the impact on the propensity to adopt AVs. Sensitivity analysis offers a quantitative approach to assess how the output changes given a change in each input. It increases the understanding of the relationships between variables in the model and helps identify important covariates that can significantly impact the endogenous variable of interest to this study.

In this study, the sensitivity analysis is performed by computing marginal effects. A marginal effect measures how the outcome variable changes with one unit change in a covariate while controlling for all other covariates. In ordinal logistic models with a nonlinear link function, model parameters cannot be interpreted as marginal effects in the way they are carried out in ordinary linear regression. Simply identifying marginal effects at the link function scale (e.g., odds ratio scale for ordinal logistic model) rather than at the probability scale provides limited information [39]. Thus, probability-based marginal effects—average marginal effects (AMEs) and marginal effect at mean (MEM)—are used here. AME computes the marginal effect of the explanatory variable for each observation and then calculates the average probability change. MEM computes the marginal effect of the explanatory variable x, setting all other variables to their mean.

3.3. Monte Carlo Simulations

The impact of combinations of variables and the combined impact of the household population decisions needs to be examined when setting public policies and assessing the region-wide impact of micro-decisions. Applying the ordinal logistic model to the synthetic population, the probabilities of a household being in the three categories (i.e., non-adopter, late adopter, and early adopter) are predicted. Rather than assigning categories based on the highest probability for each household, Monte Carlo simulation is used to introduce variability. One hundred simulations were generated for each household; in each simulation, a random number r between 0 and 1 (where $r \sim U[0,1]$, uniformly distributed between 0 and 1) was generated and compared with the cumulative probability to assign the category. If the random number r is not more than $P(Y \leq 1)$, the household is classified as non-adopter; if the r is between $P(Y \leq 1)$ and $P(Y \leq 2)$, it is classified as late adopter; otherwise, it is classified as early adopter. The mathematical formulation is as follows:

$$\text{category} = \begin{cases} \text{non-adopter} & r \leq (Y \leq 1) \\ \text{late adopter} & P(Y \leq 1) < r \leq P(Y \leq 2) \\ \text{early adopter} & r > P(Y \leq 2) \end{cases}$$

For example, in a set of 100 simulations for a household, the household might be classified as a non-adopter for 16 times, a late adopter for 62 times, and an early adopter for 22 times. In each simulation, measures such as total VMT replaced by electric AEVs for all households and GHG emission reduced by all households can be computed to assess the impact of AV adoption at the aggregate level. With 100 simulations, the mean and variance of these measures can also be obtained to check for robustness.

4. Results

4.1. Ordinal Model Results

The ordinal logistic model was estimated using the R package 'MASS' (version 7.3). The model was assessed using a likelihood ratio test; a p-value less than 0.001 suggests a good overall model fit. In addition, the concordance index (a metric to evaluate the prediction of the model) is 0.723, indicating that the model has good performance and fits the data well by the standards of transport choice modeling.

The dependent variable is influenced by a variety of explanatory variables. Table 3 presents the regression coefficients for variables that are significantly different than zero at a 90% confidence level or above. The sign of the estimate is behaviorally intuitive and aligns with expectations. Males are more likely to be an early adopter, as are young and highly educated adults. This finding is consistent with the literature [13]. The correlation between household income and AV adoption is well established, suggesting that wealthier households are usually the first to have access to expensive new technologies [13]. Asian householders are more interested in AVs than non-Asians. Interestingly, having children in households where the householder is between 35 and 64 years old increases the intention to purchase AVs. However, this is not the case for householders in other age groups. Households with higher vehicle ownership have lower proclivity to own an AV and might fall into the no-adopter category [40]. Yet, households that own electric vehicles have higher propensity to adopt AEVs, which presumably can be attributed to their technology familiarity and knowledge [9]. This is also evidence of the leverage government policies have on introducing AVs through a population segment that is already participating in incentives for electrification. As for the commuting patterns, a higher telecommuting ratio is associated with a greater disposition towards AVs. Spatial heterogeneity is also observed with households residing in the county of San Francisco being more interested in AVs. However, households in counties where healthcare and social assistance industries are the leading industries (in terms of numbers of employees) have a lower proclivity to buy an AV.

Table 3. Results of the ordinal logistic model.

Variable	Est.	S.E.	*t* Value	*p*-Value	
(Intercept): Non-Adopter—Late Adopter	0.576	0.149	3.862	0.000	***
(Intercept): Late Adopter—Early Adopter	3.460	0.16	21.56	0.000	***
Male householder (0/1)	0.389	0.064	6.038	0.000	***
Householder Age (reference: 65 and above)					
Householder ages 18–34	1.369	0.107	12.786	0.000	***
Householder ages 35–64	0.314	0.076	4.138	0.000	***
Asian householder (0/1)	0.155	0.089	1.752	0.080	*
Householder with bachelor's degree or higher (0/1)	0.217	0.072	3.020	0.003	***
Number of people over 15-years-old in the household	−0.129	0.049	−2.605	0.009	***
Number of students in the household	0.431	0.076	5.653	0.000	***
Lifecycle: householder ages 35–64 with children (0/1)	0.484	0.097	4.987	0.000	***
Household income (reference: below 75 k)					
Household income between 75 k and 100 k	0.272	0.100	2.710	0.007	***
Household income between 100 k and 150 k	0.543	0.096	5.665	0.000	***
Household income between 150 k and 200 k	0.632	0.117	5.387	0.000	***
Household income between 200 k and 250 k	0.697	0.143	4.869	0.000	***
Household income 250k and more	1.035	0.139	7.448	0.000	***
Number of vehicles in the household	−0.091	0.039	−2.345	0.019	**
Own electric vehicle(s) (0/1)	1.039	0.076	13.685	0.000	***
Telecommuting ratio	0.332	0.128	2.598	0.009	***
San Francisco County (0/1)	0.543	0.216	2.510	0.012	**
Healthcare and social assistance industry (0/1)	−0.296	0.111	−2.659	0.008	***
Observations	4248				
Likelihood ratio test	# (20) = 835.56, $p < 0.001$				
Concordance index	0.723				

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Est.: estimate, S.E.: standard error; (0/1) indicates binary variables.

4.2. Sensitivity Analysis Results

The analysis presented in Figure 2 clearly reflects the role of variables in differentiating early adopters from non-adopters. One of the most important quantitative roles in the propensity to be an early AV adopter is the ownership of an EV, in addition to young householders between 18 and 34 years old. Moreover, this propensity is also influenced positively by the telecommuting mix in the household, suggesting that the ability to multi-task and the flexibility of daily schedules are an important determinant of mode choice [41]. We also find that some places in California are far more likely to have households with a higher propensity to be the early adopters of AEVs. All this supports the idea that the niche market that will adopt AVs will most likely be a wealthy, technologically savvy, and relatively young market segment living in places with high technology firms (e.g., San Francisco). Ethnicity also plays a role in the adoption of AVs, with Asian individuals being more likely to be early adopters. People in the very large age group (35 to 64 years old) with children in the household are more likely to be non-adopters of AVs. The impact of the distribution of employment types in each county supports the idea that adoption of AVs in California will show substantial spatial heterogeneity requiring region-specific policies along the same directions of EVs [42]. In addition, the income effect is similar to that of other advanced technologies such as Urban Air Mobility [43].

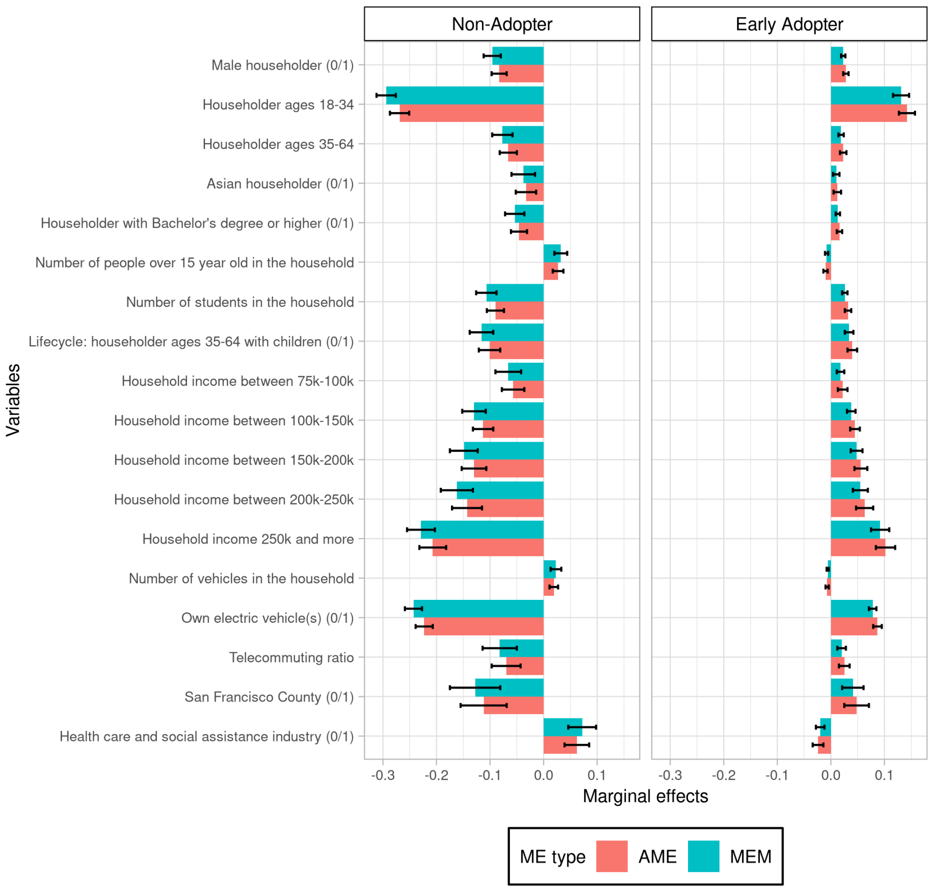


Figure 2. Marginal effects for all covariates in change of probability of being "non-adopters" and "early adopters".

4.3. Microsimulation Results

4.3.1. AEV Market Share and Replacement Rate

For each simulation, the market share of non-adopters, late adopters, and early adopters is computed, assuming only one vehicle will be replaced. Further, the replaced vehicle characteristics (e.g., mileage accrual and number of trips) are assigned to an AEV with the assumption they will be utilized similarly as the replaced vehicle. This assumption appears to be crude given that AEVs are expected to influence daily activity travel patterns and might be adopted and utilized differently [44,45], resulting in heterogeneity (e.g., high-income households might adopt more than one AEVs, while low-income households might own zero AEVs), which is not accounted for in the analysis. However, recent evidence in the space of electric vehicles (also an emerging technology) indicates that they are utilized as much as gasoline vehicles are currently [46]. Figure 3 is the average market share (percentage) of the three categories as well as the variation in the percentage for the 100 simulations. Non-adopters account for about 40 percent of the market, while late adopters are approximately 45 percent and early adopters a little over 10 percent. The variation of the market share for categories is very small across simulations (the standard deviations are less than 0.2% of their mean market share, so the error bars appear to overlap as one line for each category in Figure 3), suggesting stability of the simulation algorithm employed here. The average number of vehicles in a household and their annual mileage were also computed and reported in Figure 4. It should be noted that early adopters on average have more vehicles in their households when compared to non-adopters and late adopters. A similar pattern is observed for household annual VMT. Interestingly, non-adopters and late adopters have higher annual VMT compared to the number of vehicles owned. The plausible explanation for that pattern is that multiple household members might be using the same vehicle to meet their daily travel needs, thus resulting in higher annual VMT compared with the number of vehicles that the household owns.

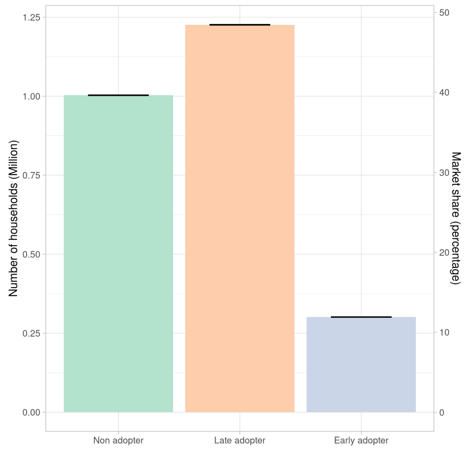


Figure 3. AEV market share and variation (error bars in black) based on simulations.

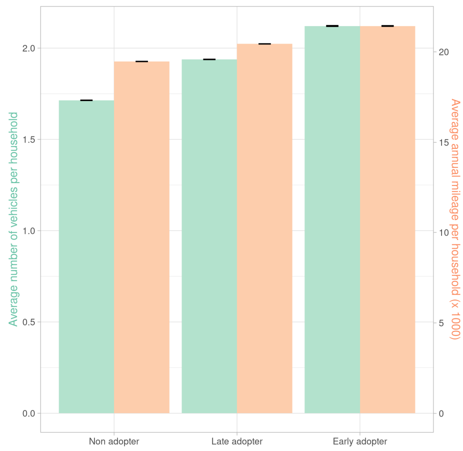


Figure 4. Average number of vehicles and average annual mileage per household for different type of AEV adoption.

4.3.2. Replacement Strategy by Vehicle Characteristics

There is considerable uncertainty about the availability of AEVs for consumers, regulations and incentives for residential locations, and type of transaction and preference for households in purchasing and using AEVs. One way to understand the uncertainty and impacts of different household strategies is to develop scenarios of how an AEV can be used to replace existing vehicles in the household. Then, for each scenario, use the simulated data to assess the impact on VMT and GHG per replacement scenario. The different vehicle replacement strategies for households having more than one vehicle are developed with underlying reasoning/motivation:

1. Replace the vehicle with the highest annual VMT (e.g., to reduce fuel cost and decrease driving fatigue).
2. Replace the vehicle with the lowest annual VMT (e.g., to avoid driving in congested urban environments).
3. Replace the electric vehicle and, if there is no electric vehicle, a random vehicle is replaced (e.g., purchase the next best technology).
4. Replace the oldest vehicle (e.g., to reduce GHG emissions and enhance household fleet reliability).
5. Replace a random vehicle from the household fleet.

At the aggregated population level, the total VMT and its percentage traveled by AEVs are computed and presented in Figure 5. For late adopters, the VMT through AEVs is about 10–17 billion miles (20–32% of the total VMT) and 2.5–7 billion miles (5–14%) for early adopters in different scenario settings. As expected, replacing the vehicle with the highest annual VMT yields the most benefits in the replacement of a vehicle for both early adopters and late adopters. However, note that due to the largest segment of late adopters, all replacement strategies for late adopters have double and triple impact on VMT replacement compared to that of early adopters. This is very important for the market structure and introduction strategies for AEV technologies, highlighting the need to start educating the public about gains of automation, pay attention to the used car market (and possibly the positive role played by the used EV car market), and to more closely examine the types of cars that are replaced. Figure 6 shows that the vehicles replaced in our scenarios are mostly passenger cars because these are the most popular vehicle body types. ICE is the predominant fuel type to be replaced, given that it is the dominant fuel type for current household vehicles (see Figure 7). The percentage of vehicles replaced in each vintage category does not vary much in different scenarios except for the oldest vehicle replacement scenarios in Figure 8.

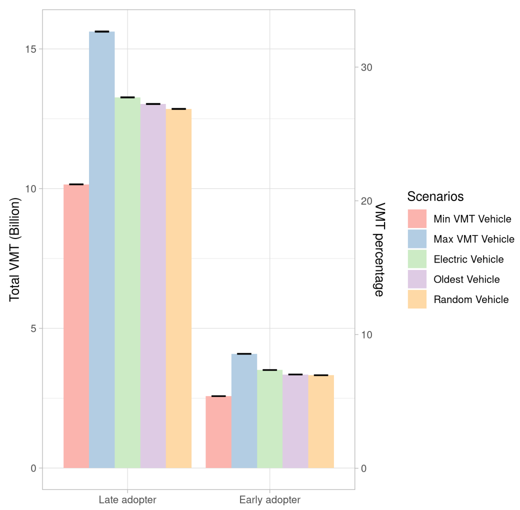


Figure 5. VMT and percentage by AEVs in different scenarios.

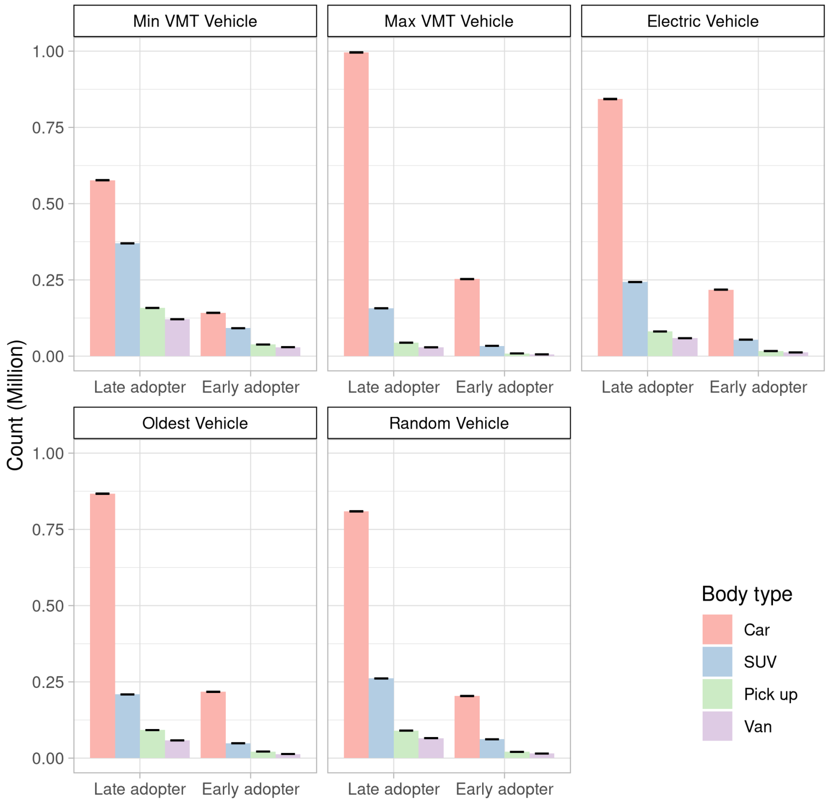


Figure 6. The number of vehicles replaced by AEVs by body type under different scenarios.

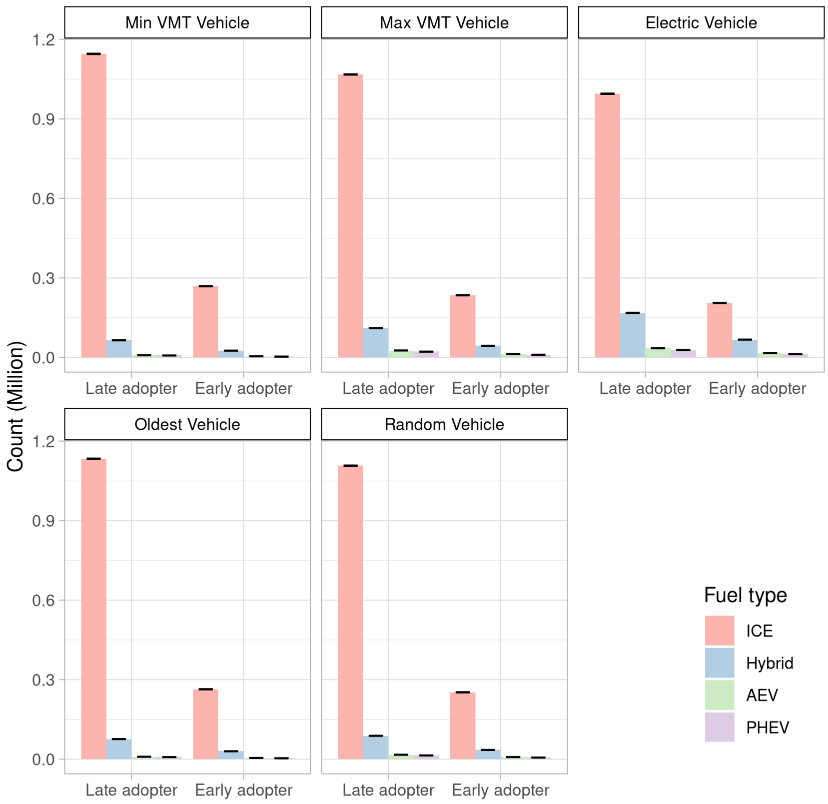


Figure 7. The number of vehicles replaced by AEVs by fuel type under different scenarios.

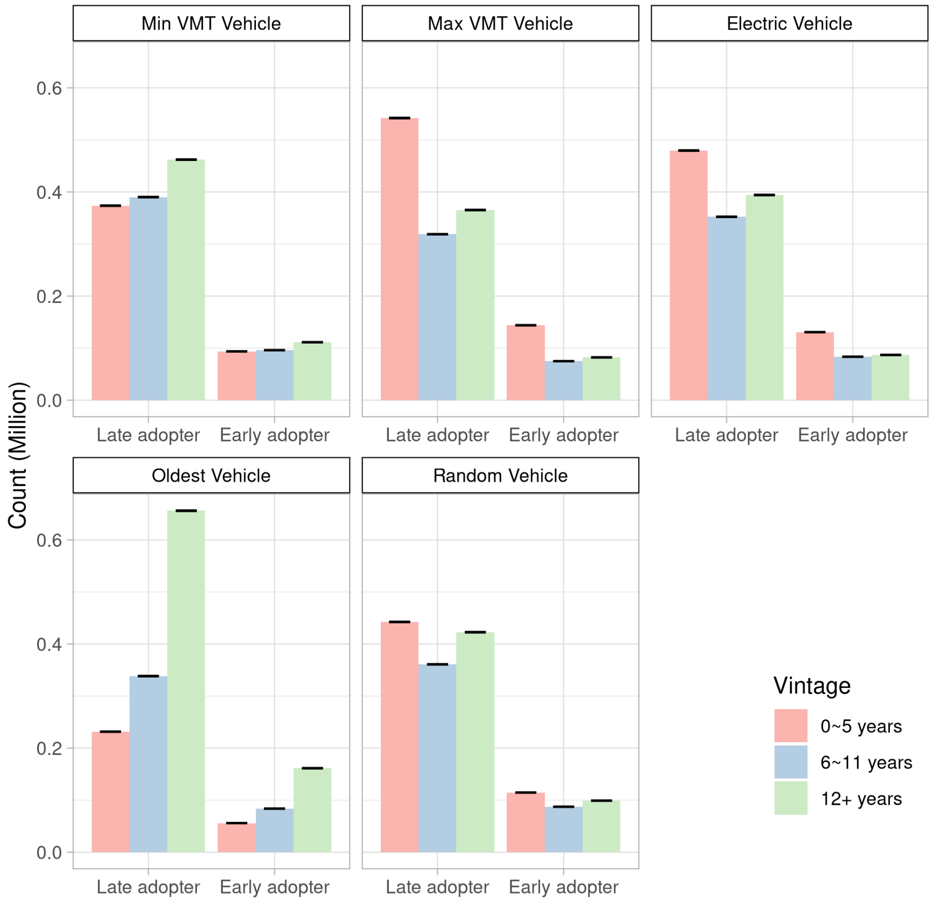


Figure 8. The number of vehicles replaced by AEVs by vintage under different scenarios.

4.3.3. GHGs Emissions

To approximately compute the maximum environmental impact of adoption of AEVs, we assume that the CO_2 tailpipe emission from ICE vehicles will be eliminated when they are replaced by AEVs. Table 4 presents the average ICE CO_2 emissions by vehicle body type and vintage, which was calculated using the data published by U.S. Environment Protection Agency [47] for each model year and vehicle body type. These values are adjusted to account for different engines and vehicle weights and to reflect real-world performance, which is typically 25 percent higher than unadjusted laboratory CO_2 values. Table 4 shows that emissions are higher for older cars, which is as expected because they have older technologies and are less efficient.

Table 4. Average ICE CO_2 emissions by vehicle body type and vintage (g/mi.)

Body Type	0∼5 Years	6∼11 Years	12+ Years
Car	316.83	364.5	418.37
Pick up	496.5	542.33	543.3
SUV	393.17	455.58	558.4
Van	416.67	450.67	552.6

After running the scenarios described above, the results of CO_2 emissions reduced when replacing ICEs with AEVs, as shown in Figure 9. On average, adopting electric AEVs (both early and late) can reduce more than 5 megatons of CO_2 yearly, which is around 30% of the total CO_2 emitted by ICEs in the synthetic population. This alone is a major finding because it shows the potential AEVs have in contributing to meeting GHG emissions targets in California reported by the California Air Resources Board—https://ww2.arb.ca.gov/our-work/programs/sustainable-communities-program/regional-plan-targets (last accessed on 3 November 2024). These targets are set regularly to meet the Senate Bill 375 requirements and are expressed as a percent change in per capita greenhouse gas emissions from passenger vehicles compared to the levels in 2005. Even if one accounts for the savings in CO_2 emissions of the early adopters alone, the contributions are remarkable and will make a difference in regions' target requirements and decarbonizing the transport sector. Moreover, providing incentives to replace older, most-used vehicles in a household will also have the added benefit of reducing contributions to other pollutants from ICEs. However, it should be noted that the increased demand on power grids, due to the transport electrification required to realize these benefits, might be substantial. To fully realize the outcomes of the scenario, it would be important to upgrade existing grid infrastructure for increased capacity, enhanced distribution networks, and the integration of renewable energy sources to meet the additional demand from the transport sector. While these impacts on the grid are critical considerations, accounting for them is beyond the scope of this study.

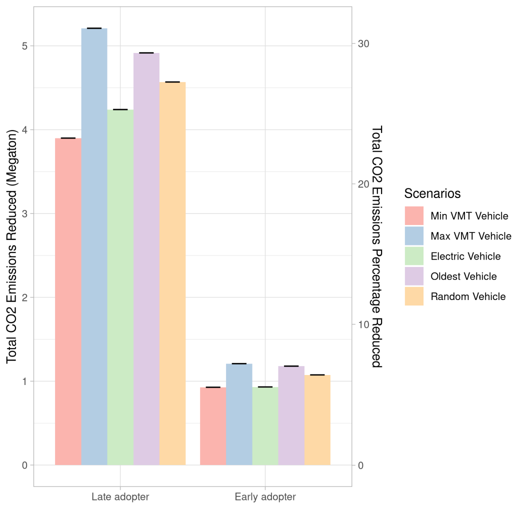


Figure 9. Total CO_2 emissions reduced and percentage when replacing ICEs with AEVs under different scenarios.

The scenarios show the benefits of replacing older vehicles and high-VMT vehicles in a household fleet. They also show the substantial benefit from early adopters motivating the recommendation of providing substantial incentives for the successful introduction of AEVs in the market. In addition, the findings here also show that late adoption of the technology further amplifies the major benefits to society in terms of fuel consumption and mitigating the climate impacts of automobile use and mobile source emissions. From a technical viewpoint, this paper shows a method to use an intention model and develop scenarios of AEV market penetration and impact assessment, applied to the first tier of regional activity-based microsimulation models. For example, see the activity-based models developed by the Southern California Association of Governments (SCAG) at https://scag.ca.gov/activity-based-model (last accessed on 3 November 2024), and by the San Diego Association of Governments (SANDAG) at https://github.com/SANDAG/ABM/wiki (last accessed on 3 November 2024).

5. Policy Implications

This study presents the demand model for AEVs and assesses its impacts on VMT and direct GHG emissions from a vehicle annual operation perspective for different consumer segments. It is observed that owners of relatively more advanced technologies are likely to endorse and adopt AEVs. In addition, individuals that are young, wealthy, and living in places that induce variety in activity participation are more likely to be early adopters of AEV technology. This segment alone can significantly contribute to a decrease in GHG emissions and should be incentivized to do so. In California, there are specific locations such as San Francisco that are more likely to have households with a higher propensity to be early adopters of AEVs. All of this supports the idea that we may need geographically differentiated incentive policies targeting wealthy, technologically savvy, young market segments living in places with high technology firms (e.g., San Francisco) to jumpstart the adoption of AEVs and create a robust new vehicle market. On the other hand, as the technology matures and starts to penetrate the market, late adopters have the highest potential to change the arithmetic of meeting regional targets set by the California Air Resources Board (CARB) in its Senate Bill 375 compliance mandates for regions.

In the replacement scenario, for late adopters, the VMT through AEVs is about 10–17 billion miles (20–32% of total VMT) and 2.5–7 billion miles (5–14%) for early adopters. Replacing the vehicle with the highest annual VMT yields the most benefits in the replacement of a vehicle for both early adopters and late adopters. This is very important for the market structure and introduction strategies for the AEV technologies pointing to a need to start educating the public about benefits of automation, attention paid to the used car market (and possibly the positive role played by the used EV car market), and the need to examine more closely the types of cars that are replaced. Further, to understand the energy implications, it is observed that adopting electric AEVs can reduce more than 5 megatons of tailpipe CO_2 emission yearly, which is around 30% of the total CO_2 emitted by ICEs in the synthetic population.

Since passenger cars have the highest annual VMT, incentives should prioritize them over SUVs, pick-up trucks, or vans. Older cars used for a higher proportion of household travel are also the types of vehicles that should be targeted (e.g., using scrappage vehicle policies). This is not new in the US and has been a successful policy initiative (similar to the Car Allowance Rebate System, also known as the "cash for clunkers" program). We should expect that passenger cars will not only be replaced, but households may switch vehicle body type in this program. This is something we could not study in this analysis and needs to be explored further by looking at the types of vehicles replaced when households purchase AEVs either in real world data collection or in hypothetical scenarios. Understanding household inclination towards vehicle body type in the context of AEVs might help automakers develop a focused, ready market as the AEV technology matures. In the context of EVs, Higgins et al. [48] found that vehicle body type significantly influences the decision-making behavior of EV consumers. Based on the findings in this study, it is also important to explore the second-hand car market and identify the propensity of people to adopt technologies after the early adopters move to more advanced options. In other words, the used vehicle market will play a substantial role in increasing the market penetration rate of AEVs by catering it to late and non-adopters and might disrupt the mobility market significantly. Further, the second-hand market can be seen as a way to accelerate technology adoption in disadvantaged communities. All of this provides added evidence of the need to combine car autonomy with electrification, even in the absence of sharing [49]. This pilot study shows that the combination of automation with electrification has the potential for major tailpipe greenhouse gas emission reduction, provided that issues raised by other research challenges are addressed [50], and reduces the uncertainty described by other authors [51]. However, we also find that using more creative sets of incentive strategies (e.g., commercial fleet scrappage programs and weighted incentivization combined with photovoltaic energy production and affordable housing policies) and developing a second-hand electric vehicle market makes sense in the adoption of technologies, as described later.

6. Conclusions

In this study, a statistical model correlating AEV adoption intention and socioeconomic and built environment attributes was estimated using the 2019 CVS survey; a sensitivity analysis was conducted to understand the importance of factors impacting AEV adoption.

Using the San Francisco Bay Area synthetic population, a microsimulation of market penetration with five household vehicle replacement scenarios assessed how the annual VMT and tailpipe CO_2 emissions associated with vehicle usage can change. It is found that adopting electric AEVs can potentially reduce more than 5 megatons of CO_2 yearly, which is approximately 30% of the total CO_2 emitted by Internal Combustion Engine cars in the region.

There is substantial additional work that needs to be conducted to set policies such as carbon tax and time-of-day charging systems that other research has explored in the context of shared autonomous electric vehicles [52]. This is because AEV reductions in GHG emissions are very sensitive to time-of-day vehicle operations, and we need to account for important parameters such as vehicle utilization and charging operations, vehicle technology, meteorological conditions, and energy generation to power the vehicles [53]. In addition, a vehicle replacement model should be integrated in the simulation since our assumption that only one existing vehicle is replaced may not accurately represent real-world scenarios. Households without any vehicles, such as individuals with age limitations or disabilities, may acquire AEVs. Additionally, households with existing vehicles may not simply replace one vehicle but, rather, replace multiple vehicles or add new ones when adopting AEVs [54]. Even more substantial, however, may be the change in travel behavior that influences both the owned and shared automobile market with strong temporal and spatial differentiation in preferences guiding behaviors. One limitation of our microsimulation is the assumption that household travel behavior—specifically, annual VMT—remains constant. In fact, as part of future work, this study seeks to simulate different types of activity–travel patterns replaced by AEV at individual levels throughout the day across space. In order to do this, existing literature [7] on the knowledge of the relationship between individuals' spatio-temporal activity–travel patterns with their dispositions to buying AEVs can be incorporated into a currently developing activity-based model for the synthetic population and vehicles (e.g., ATLAS, mentioned earlier in this paper). This study is just the beginning of a much larger microsimulation to address many of the challenges described in [51] and going further into the integration with other aspects of energy demand. One possible avenue is to consider total home energy management and expand on recent research to optimize energy management in the building sector [55]. Beyond this, using the methods developed here, researchers can possibly simulate the impact of incentives on an entire region's GHG emissions from the use of energy storage systems by households [56], explore the impact of static and dynamic pricing of battery charging at workplaces [57], and integrate in travel behavior daily simulation community energy storage centers [58]. Yet another possible research direction is in future fuels, the household propensity to consider AEVs and hydrogen-powered vehicles, and the impact on VMT and GHG emissions to complement aggregate studies such as [59]. Moreover, this study is limited in scope as it specifically focuses on assessing the impact of replacing ICEs with AEVs from a "behavioral utilization" and tailpipe emission perspective. We acknowledge that this approach excludes a comprehensive evaluation of the entire lifecycle emissions associated with AEVs, including factors such as electricity generation, battery production, and other upstream and downstream processes. Additionally, the study does not account for how factors such as temperature, driving habits, and road conditions may influence the real-world performance and energy consumption of AEVs. Therefore, the findings presented in this study provide an essential but partial perspective on the environmental impact of the transition to electric AEVs. A more comprehensive assessment would require the incorporation of these broader life-cycle considerations to provide a more holistic understanding of the GHG emissions associated with AEV adoption.

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administration, K.G.G., S.R. and S.S.; Funding acquisition, K.G.G., S.R., S.S. and C.A.S. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The raw data used for the development of the models underpinning this analysis are publicly available: the 2019 California Vehicle Survey data can be found at https://www.nrel.gov/transportation/secure-transportation-data/tsdc-2019-california-vehicle-survey.html (last accessed on 3 November 2024). The simulated datasets used in the analysis for this article are not readily available because the data are part of an ongoing model development process, the publicly released version of which has surpassed the version of the data generated for this analysis. Requests to access the datasets should be directed to the authors and will be considered based on the purpose and specific data being requested.

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