Transportation Research Part C 120 (2020) 102774

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Synthesizing neighborhood preferences for automated vehicles

Wenwen Zhang [a,*], Kaidi Wang [b], Sicheng Wang [a], Zhiqiu Jiang [c], Andrew Mondschein [c], Robert B. Noland [a]

[a] *Edward J. Bloustein School of Planning and Public Policy, Rutgers University, United States*
[b] *Department of Urban Affairs and Planning, Virginia Polytechnic Institute and State University, United States*
[c] *Department of Urban and Environmental Planning, University of Virginia, United States*

ARTICLE INFO

Keywords:
Preferences
Shared automated vehicles
Private automated vehicles
Machine learning
Population synthesizing

ABSTRACT

Automated Vehicles (AVs) have gained substantial attention in recent years as the technology has matured. Researchers and policymakers envision that AV deployment will change transportation, development patterns, and other urban systems. Researchers have examined AVs and their potential impacts with two methods: (1) survey-based studies of AV preferences and (2) simulation-based estimation of secondary impacts of varied AV deployment strategies, such as Shared AVs (SAVs) and Privately-owned AVs (PAVs). While the preference survey literature can inform AV simulation studies, preference study results have so far not been integrated into simulation-based research. This lack of integration stems from the absence of data that measure preferences towards PAVs and SAVs at the neighborhood level. Existing preference studies usually investigate adoption likelihood without collecting appropriate information to link preferences to precise locations or neighborhoods. This study develops a microsimulation approach, incorporating machine learning and population synthesizing, to fill this data gap, leveraging a national AV perception survey (NAVPS) and the latest National Household Travel Survey (NHTS) data. The model is applied to San Francisco, CA, and Austin, TX, to test the concept. We validate the proposed model by comparing the spatial distributions of synthesized ride-hailing users and observed ride-hailing trips. High correlations between our synthesized user density and empirical trip distributions in two study areas, to some extent, verify our proposed modeling approach.

1. Introduction

AV technology is positioned to potentially transform transportation, development patterns, and other urban systems (Fagnant and Kockelman, 2015). The trajectory of urban development may vary depending on adoption rates, especially based on preferences towards owning (private autonomous vehicles, PAVs) or shared autonomous vehicles (SAVs) (Fagnant and Kockelman, 2015). Many AV simulation studies suggest that SAVs are more sustainable compared with PAVs: SAVs can reduce parking demand (Zhang and Guhathakurta, 2017), curb additional vehicle ownership (Fagnant and Kockelman, 2014; Zhang and Guhathakurta, 2018a), generate fewer empty Vehicle Miles Travelled (VMT) (Zhang et al., 2015a), and correspondingly lead to reduced emissions of greenhouse gases and criteria pollutants, especially if powered by electricity (Greenblatt and Saxena, 2015). However, in reality, the impact of AVs is highly dependent on how many users will opt to share, either their vehicle or rides with others (Gkartzonikas and Gkritza, 2019).

* Corresponding author.
E-mail addresses: wenwen.zhang@ejb.rutgers.edu (W. Zhang), kaidi@vt.edu (K. Wang), sicheng.wang@rutgers.edu (S. Wang), zj3av@virginia.edu (Z. Jiang), mondschein@virginia.edu (A. Mondschein), rnoland@rutgers.edu (R.B. Noland).

https://doi.org/10.1016/j.trc.2020.102774
Received 28 February 2020; Received in revised form 17 August 2020; Accepted 21 August 2020
Available online 17 September 2020

Although a wealth of user preference surveys and mode choice experiments have been conducted to understand key factors influencing the adoption of AVs, there remains a data gap regarding the spatial distributions of SAV and PAV adopters. Such knowledge is critical to fuel more robust AV simulations and support policymaking to encourage the adoption of SAVs.

Motivated by the lack of data about how AV preferences map to local neighborhoods, we develop a generalizable microsimulation framework to synthesize neighborhood-level preferences towards SAVs and PAVs. This work serves as an anchor point for future research seeking to merge existing AV preference data with simulation studies. The paper is organized as follows. The next section reviews the existing literature to identify research needs. Section 3 describes the proposed modeling framework and data sources used in this study. Section 4 elaborates on the selection of study area and model implementation. Section 5 discusses synthesized SAV and PAV results and compares the synthesized ride-hailing results (i.e., byproducts of the model) with the ride-hailing service adoption patterns to determine the robustness of the proposed model. The last section summarizes the performance of the proposed model and discusses directions for future research endeavors.

2. Literature review

Prior transportation and urban planning studies on AVs can be divided into two primary streams. The first stream examines how travelers may adopt this technology, as the short-term and long-term impacts of AVs depend on people's preferences. Early studies applied descriptive analysis to online survey data or summarized focus group meeting results to obtain a general picture of the opinions towards AVs and willingness to pay for AV technology in different countries, including the United States (Abraham et al., 2016; Howard and Dai, 2014; Power et al., 2012, 2013; Vallet, 2013; Zmud and Sener, 2017), United Kingdom (Begg, 2014; Ipsos, 2014), Australia (Schoettle and Sivak, 2014a), China, Japan, India (Schoettle and Sivak, 2014b), and other countries across the world (Brown et al., 2014; Kyriakidis et al., 2015).

Recent in-depth survey studies quantify how demographic, socioeconomic attributes, and existing travel behavior may influence the willingness to adopt AVs, using discrete choice models, such as Logit and Probit models (Bansal and Kockelman, 2017, 2018; Lavieri et al., 2017; Payre et al., 2014; Shin et al., 2015; Spurlock et al., 2019; Wang and Akar, 2019; Wang et al., 2020), and social behavior models, such as Structural Equation Models (SEMs) based on behavior theory models, such as Unified Theory of Acceptance and Use of Technology (UTAUT) (Asgari et al., 2018; Choi and Ji, 2015; Hassan et al., 2019). The majority of model results suggest that young, tech-savvy, and well-educated males, who are currently urban residents and suffering from traffic congestion, expressed higher interest in the use of AVs, as summarized in the literature review conducted by Gkartzonikas and Gkritza (2019). Senior residents are found to be more reluctant to accept the technology, due to safety concerns and a lack of awareness of the concept, compared with their younger counterparts (Hassan et al., 2019; Wang et al., 2020). Results from choice experiment survey-based studies show respondents with different socioeconomic, attitudes, and travel patterns may prefer different business models of AVs, such as SAVs and PAVs. After controlling for service characteristics, such as travel costs, the value of in-vehicle time, and waiting time (correlated with individual income) and trip attributes, such as trip purpose, it is found that younger and well-educated travelers who do not enjoy driving, have environmental concerns, and pro-technology attitudes are more likely to adopt SAV mode (with or without dynamic ridesharing) (Haboucha et al., 2017; Krueger et al., 2016). A recent U.S. national study reveals that the attitudes towards SAVs and PAVs also tend to vary across regions (Jiang et al., 2020). In short, the existing AV stated-preference survey literature suggests there is considerable heterogeneity in public preferences towards AVs in general, as well as in the adoption of PAVs and SAVs.

The other stream of literature explores the secondary impacts of SAVs and PAVs using agent-based simulation. Specifically, research has examined the short-term (e.g., congestion, travel affordability, safety, etc.), medium-term (e.g., vehicle ownership, travel behavior adaptation, etc.), and long-term (e.g., land use changes, real estate market, social equity, etc.) impacts of PAVs and SAVs (see [Milakis et al., 2017] for a detailed discussion of secondary impacts). Simulation experiments suggest that SAVs are more sustainable compared with conventional vehicles and PAVs. From the short-term perspective, SAVs hold great potential to reduce travel costs (both operation and in-vehicle time costs) (Bösch et al., 2018; Burns et al., 2013) and curb demand of parking infrastructure (Kondor et al., 2018; Martinez and Crist, 2015; Zhang et al., 2015b; Zhang and Guhathakurta, 2017). From the mid-term perspective, SAVs can reduce vehicle ownership (Chen et al., 2016; Fagnant and Kockelman, 2014; Zhang et al., 2015b) and transportation emissions if the willingness to share rides is high (Greenblatt and Saxena, 2015; Taiebat et al., 2018; Wadud et al., 2016). If PAVs, however, become dominant, then most studies suggest less vehicle ownership and less potential for reduced parking needs (Wang et al., 2019; Zhang and Guhathakurta, 2018a). Both SAVs and PAVs are simulated to substantially increase Vehicle Miles Traveled (VMT) generation (Harper et al., 2018; Wang et al., 2019; Zhang and Guhathakurta, 2018a). SAVs are found to generate less induced empty VMT (or zero-occupied VMT) compared with PAVs (Zhang and Guhathakurta, 2018a). The debate remains for long-term impacts regarding whether AVs will contribute to more urban sprawl or encourage compact development, depending on the dominant business model of AVs. Some argue that SAVs may result in denser neighborhoods, as the expected waiting time in sprawled communities is significantly higher. PAVs, on the other hand, may induce sprawl due to a reduction of in-vehicle travel time costs. However, the results are not conclusive due to a significant amount of uncertainty embedded in long-term decision making. Zhang and Guhathakurta (2018b) suggest that households may relocate to more desirable neighborhoods that are further away from work locations due to the reduction in travel costs brought by SAVs. Additionally, households may relocate in different directions (away or closer to downtown) depending on the characteristics of the neighborhoods and their preferences.

These two streams of literature, however, are not integrated. Most of the existing agent-based simulation models are developed based on either a homogeneous technology adoption assumption (Zhang et al., 2015b; Zhang and Guhathakurta, 2017) or a 100% market penetration level (Martinez and Crist, 2015). Such assumptions and simplifications are recognized as one of the model limitations that merit future improvement in the majority of AV simulation studies (Fagnant and Kockelman, 2018; Martinez and Crist,

Table 1
Comparison of Census Data with NAVPS data.

	Census	NAVPS
Income		
Under $25,000	19%	19%
$25,000–$50,000	21%	24%
$50,000–$100,000	30%	32%
$100,000–$150,000	15%	13%
$150,000–$200,000	7%	6%
$200,000+	9%	5%
Gender		
Female	51%	50%
Male	49%	50%
Age		
18–24	12%	13%
25–44	34%	35%
45–64	33%	35%
65+	21%	17%
Urban vs. Rural		
Urban	80.8%	80.7%
Rural	19.2%	19.3%

2015; Zhang and Guhathakurta, 2017; Zhang and Wang, 2020). These assumptions are introduced because current AV preference models are developed to understand statistical inferences of various attitudinal variables (e.g., tech-savvy, preferences for home location, etc.) on AV adoption decision-making. These variables are not available in typical travel surveys nor ACS data, rendering it impossible to simulate PAV and SAV preferences for agents. Thus, there is a need to merge the two streams of literatures, i.e., generate neighborhood-level PAV and SAV preferences, and introduce heterogeneous agents into the simulation. This study contributes to the existing literature by proposing a transferrable methodology to impute neighborhood-level AV preferences to fuel more robust SAV and PAV simulations.

3. Model framework and data

The proposed three-step microsimulation framework is developed based on data from three sources. In this section, we first briefly introduce these datasets before elaborating on the details of the proposed model. The data inputs include (1) a National AV Preference Survey (NAVPS), (2) the 2017 National Household Travel Survey (NHTS), and (3) the 2018 5-year American Community Survey (ACS) data. NAVPS is an attitudinal survey conducted via an online panel supplied by Qualtrics with a nationally representative sample in September 2018 by Wang, Jiang, Noland, and Mondschein (2020). The survey instrument contained 42 questions and took, on average, 8 min to complete. It asked attitudinal questions about the preferences towards PAVs and SAVs, including the general attitudes towards AVs, the willingness to purchase an AV, the willingness to use an AV as a taxi service, and the willingness to share a ride with strangers in an AV taxi. In the NAVPS, AV is defined as "a computerized vehicle that can drive itself and does not need a person operating the vehicle." PAVs are defined as privately owned AVs. SAVs are defined as AVs that are not owned and need to be shared with strangers (Wang et al., 2018).

Moreover, NAVPS also collected information about respondents' socioeconomic, demographic, and a variety of attitudinal and behavioral attributes, such as the adoption of new technologies, the perceptions of risks, preferences for driving, and attitudes towards traffic regulations. The NAVPS data includes 834 individuals (age 18 and above) across the United States. After eliminating invalid and missing data, the dataset includes 721 completed responses. The socioeconomic and demographic variables in NAVPS are consistent with the ACS data, as shown in Table 1. More descriptive analysis of the collected data and survey design can be found in Wang et al. (2020) and Jiang et al., (2020).

The 2017 NHTS data are the latest travel survey released by the Federal Highway Administration (FHWA). The data consist of travel behavior, socioeconomic, and demographic information. There are 129,696 sampled households and 264,234 individuals in the NHTS data across the country. Several Core Based Statistical Areas (CBSA), such as San Francisco, Austin, and Atlanta, etc. have a larger sample size, as the local government purchased add-on samples. A series of household and individual-level attributes are shared by the NAVPS and NHTS datasets. The NHTS data, however, do not include preferences towards any business model of AVs. Lastly, the ACS data are released by the U.S. Census Bureau and provide marginal distributions of various socioeconomic and demographic attributes at a range of geographic unit levels, such as block groups, census tract, county, and state.

In the proposed three-step microsimulation, we will first train machine learning models to predict PAV and SAV preferences using the NAVPS data, with socioeconomic and built environment variables shared by the 2017 NHTS data. Second, we will apply the best-trained model to impute PAV and SAV preferences for each adult (i.e., above 18) in the NHTS person dataset. Finally, we synthesize households and populations using the NHTS data with imputed PAV and SAV preferences and current use of ride-hailing apps as the seed matrix and ACS data as the marginal controls. We finally obtain the spatial distribution of PAV and SAV adoption preferences at the geographic units that are used to generate the synthetic population.

3.1. Machine learning PAV and SAV preferences

We used various machine learning classifiers to impute the willingness to adopt PAVs and SAVs using household- and individual-level variables shared by NAVPS and NHTS data. The dependent variables/target features are binary, i.e., likely or not likely to purchase AVs and/or use SAVs. The shared socioeconomic (e.g., income, household size, family life cycle), demographic (e.g., race and ethnicity), and past travel behavior variables (e.g., current commute mode and experiences with ride-hailing apps), and built environment variables (e.g., population and employment density, regional dummies) are used as explanatory variables to predict preferences for PAVs and SAVs. The categorical variables are transformed into a series of binary variables before training the model. The continuous variables are normalized, as some machine learning models are sensitive to the unit of variables. The NAVPS data are unbalanced, i.e., only a small portion of the respondents expressed interest in adopting either PAVs (i.e., 33.4%) or SAVs (i.e., 24.2%). To enhance the performance of machine learning classifiers, we randomly downsampled the respondents who are not interested in either SAVs or PAVs and generated a balanced dataset for machine learning experiments. The classifiers (as well as their hyper-parameters, shown in Appendix A, Table 3) are trained using the 10-fold cross-validation method to prevent model overfitting. Examined models include Decision Tree Classifier (Swain and Hauska, 1977), Extra Tree Classifier (Geurts et al., 2006, p. 20), K-Neighbors Classifier (Keller et al., 1985), Support Vector Classifier (Platt et al., 1999), Logistic Regression, Ridge Classifier (Hoerl and Kennard, 1970), Random Forest Classifier (Breiman, 2001), and Gradient Boosting Classifier (Friedman, 2002). We used average accuracy to select the best model, as the training data are already balanced before model experiments. The best-trained models for PAV and SAV preferences are then applied to NHTS person data to impute the likelihood to adopt PAVs and SAVs for individuals above the age of 18. The NHTS households and person data (with imputed PAV and SAV preferences) are subsequently used as seed matrices for population synthesizing. We used Python 2.7 and Scikit-learn 0.20.0 package (Pedregosa et al., 2011) to implement the aforementioned models and impute AV preferences.

3.2. Population synthesizing

The final NHTS data outputs from the previous step, together with the marginal distribution of socioeconomic variables obtained from ACS data, are then used to generate a synthetic population of households. In other words, the NHTS records with imputed willingness to adopt SAV and PAV variables are replicated to produce a synthetic population of household and population agents in the region that reproduces the distributions of socioeconomic and demographic variables as depicted in the ACS data. The NHTS data provide the joint distribution of these socioeconomic and demographic variables. The synthetic population can also be generated to be representative across administrative levels (e.g., census blocks, block groups, tracts, and counties.) or any other spatial boundaries (e.g., Traffic Analysis Zones [TAZs]) given the availability of marginal distributions of socioeconomic and demographic variables. In this study, the synthetic population is generated, such that the population distribution is matched at the census tract level. This step is implemented in software PopGen 1.1 (Konduri et al., 2016), which uses the Iterative Proportional Updating (IPU) algorithm to ensure socioeconomic and demographic variables at both household and individual levels are matched to their marginal distributions. The final synthetic households and population include both the controlled variables, as well as existing ride-hailing behavior and preferences for PAVs and SAVs. The neighborhood-level AV preferences and ride-hailing users are then obtained by aggregating the synthesized households and household members.

4. Model implementation

To test the concept, we applied the proposed machine learning-based microsimulation approach to two study areas (San Francisco, CA, and Austin, TX) to validate the model. The two areas are selected for the following reasons. First, the selected cities are well-sampled in the 2017 NHTS, with 2309 households sampled in San Francisco and 2168 households sampled in Austin. Thus, the 2017 NHTS samples for these areas will serve as robust seed matrices for population synthesis. Second, the two study areas have different uptakes of ride-hailing services. San Francisco, with a 26.49% adoption rate (calculated based on the weighted sample), ranked the highest in the nation. The adoption rate in Austin is only 11.23%, slightly below the national average (i.e., 12.3% in Core-based Statistical Areas [CBSAs]). Finally, the spatial distribution of ride-hailing trips is available in these two areas from various sources, which will be used to validate the synthesized ride-hailing users.

4.1. Data preparation

We first identified and recoded shared variables in the NAVPS and 2017 NHTS datasets to harmonize their measurements and units (See Appendix A, Table 4). There are 12 common variables from the two datasets, including age, gender, ethnicity (i.e., Hispanic), race, educational attainment, commute mode, experiences with ride-hailing Apps, household income, size, and vehicle ownership. Some variables from the NAVPS, such as the number of children and generation (e.g., Millennials, Generation X, Baby Boomers, etc.), are not directly available in the 2017 NHTS data. We imputed these variables based on household information or personal information. We recoded some shared variables, as there are discrepancies in the categories of the data. For instance, household size from the NAVPS is classified into six categories (i.e., 1, 2, 3, 4, 5, and 6+), and the variable is numeric in the NHTS data. Therefore, we categorize the NHTS household size into seven categories to align with the NAVPS data. A Similar method also applied to other variables, such as

Table 2
Ride-hailing Frequency Variable Recoding.

Ride-hailing Frequency in NAVPS	Ride-hailing Frequency in NHTS	Recoded Category
Never, A few times per year	0	Never or rare Users
Once per month	1–2	Occasional Users
Once per week	3–6	Frequent Users
Several times per week	>6	High frequency Users

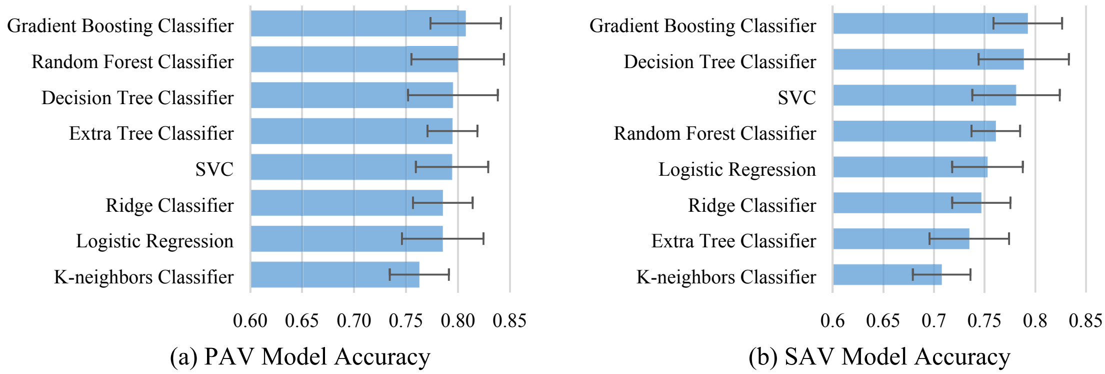


Fig. 1. Machine Learning Model Results.

race, household vehicle count, commute mode, educational attainment, and income variables. Additionally, the survey questions targeting existing ride-hailing behavior are different for the two data sources. In the NAVPS, respondents were asked about the frequency of requesting ride-hailing services, such as "Never", "A few times per year", "Once per month", etc. While, in the NHTS data, respondents were asked to provide the number of times using any ride-hailing service in the past 30 days, rendering a numeric ride-hailing frequency variable. We recoded the ride-hailing variables based on the approximated frequency, as shown in Table 2. The recoded categorical variables are then split into binary variables by category. The numerical variables are standardized based on the means and standard deviations of the pooled data (i.e., combining the NAVPS and NHTS data). In addition to the above common variables, we also incorporated some built environment variables, such as regional, city, state dummies, and population and employment densities.

4.2. Machine learning model training

Fig. 1a displays machine learning results for PAV preferences. For each model type, we only show the best cross-validated accuracy among all the combinations of tested hyperparameters. The standard deviations of the testing accuracies are displayed using error bars. Gradient Boosting Classifier, with an average accuracy of 0.807, slightly outperforms the other models. The average accuracy of the Random Forest Classifier is only marginally smaller than the Gradient Boosting Classifier (i.e., 0.800 vs. 0.807). However, the Random Forest Classifier has a slightly larger variation in predictive power. Therefore, we used the Gradient Boosting Classifier to impute the PAV preferences in the NHTS data. The cross-validated true positive rate (i.e., percent observed to be interested in adopting PAV and predicted to be interested) is 70.3%. The true negative rate of the model (i.e., percent observed to be not interested [e.g., neutral and prefer not] in adopting PAVs and predicted to be not interested) is 85.6%. This indicates that the predictive power of the Gradient Boosting Classifier is quite high.

The machine learning results for SAV preferences are shown in Fig. 1b. Similar to the results of the PAV preference models, the performance of the Gradient Boosting Classifier exceeds the other models. The overall predictive power of the model is also close to the PAV models, as the average accuracy is around 0.792. Despite comparable overall model performances, the true positive rate for the best SAV model, however, is 63.1%, and the true negative rate is 92.9%. This suggests the model is conservative and may have a tendency to under-predict the number of SAV adopters. This may be attributed to the fact that fewer respondents in the NAVPS data show interest in the adoption of SAVs, rendering a smaller modeling sample size (as we downsampled the not-interested samples to match the number of interested samples). Future model implementation efforts could use a larger survey sample to address this issue. However, in general, the SAV model still outperforms the widely adopted simulation approach, i.e., randomly assign travelers to adopt SAVs. We applied the trained PAV and SAV Gradient Boosting models to the NHTS sampled individuals in San Francisco and Austin CBSAs for population synthesizing.

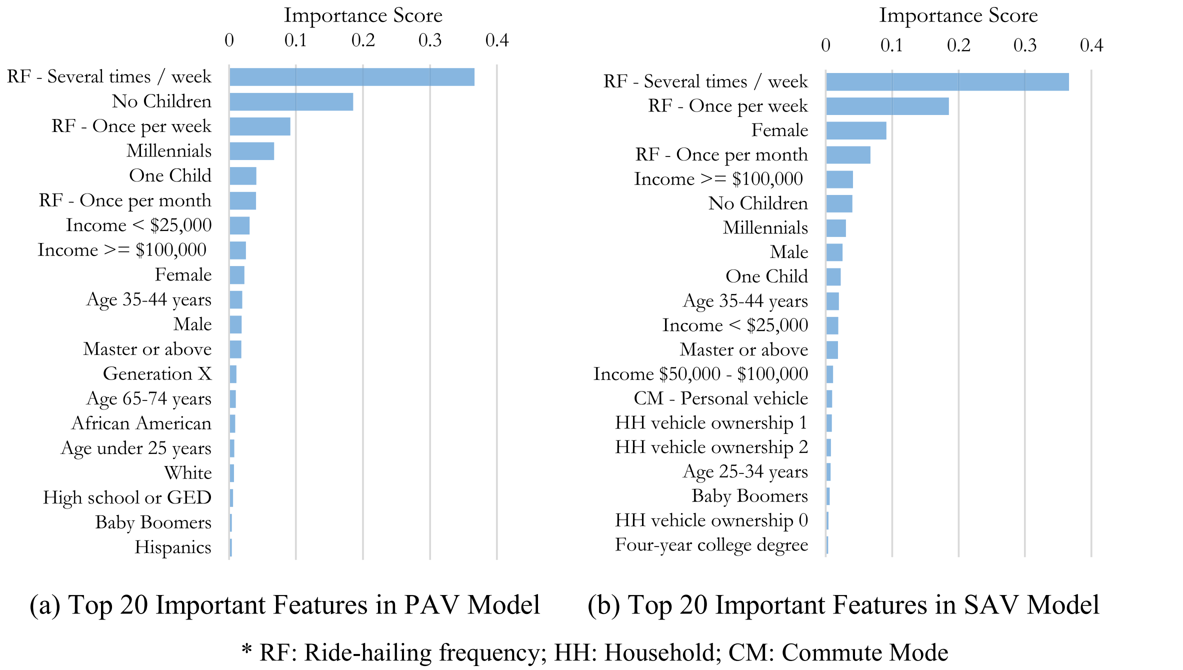


Fig. 2. Top 20 Predictive Attributes for each Model. *RF: Ride-hailing frequency; HH: Household; CM: Commute Mode.

4.3. Population synthesizing

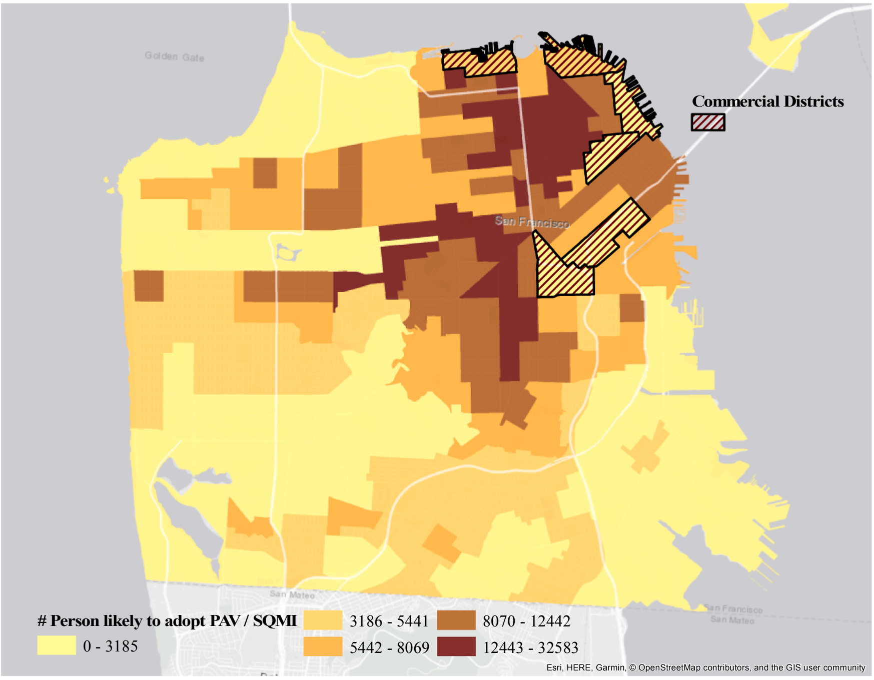
The populations of households in the two study areas are synthesized through the PopGen 1.1 software package. The inputs include (1) a seed matrix, i.e., NHTS sampled individuals (with imputed SAV and PAV preferences) and households from the two CBSAs and (2) marginal controls, i.e., the ACS data. The software estimates a weight for each household in the seed matrix, which is later used to duplicate the NHTS sampled household and individuals into a full synthetic population for the two study areas. The control variables are selected based on the variable importance scores from the Gradient Boosting models (i.e., variables' contributions to the correct prediction of SAV and PAV preferences). By controlling these predictive variables, the synthesis process can provide representative populations with distributions of AV preferences that reflect possible PAV and SAV adoption patterns in the two regions.

The top 20 most important features from the PAV and SAV Gradient Boosting models are shown in Fig. 2. For both models, the adoption of AVs, in general, is highly correlated with the current travel experiences with ride-hailing Apps. Frequent ride-hailing service users (i.e., several times per week) are most predictive in both SAV and PAV models. "Frequent" and "Occasional" users are also correlated and ranked as the top six predictive features. However, existing ride-hailing behavior is more correlated with SAV preferences, as three of the top five features from the SAV model are different categories of ride-hailing frequencies, as shown in Fig. 2b. Such a result is expected, as the envisioned SAV system, to some extent, is a replicate of the existing ride-hailing service but without human drivers. The presence of children and age tend to be more critical in PAV models (see Fig. 2a) while, gender and income are more important factors for SAV preferences. This result is in line with the existing statistical model outputs, which suggest that higher income and being female lead to lower preferences for SAVs (Wang et al., 2020). Other predictive features include educational attainment, household vehicle ownership, race, and ethnicity, which are also found to be associated with preferences of AVs in prior studies (see Gkartzonikas and Gkritza (2019) for a detailed review of results from previous preference surveys).

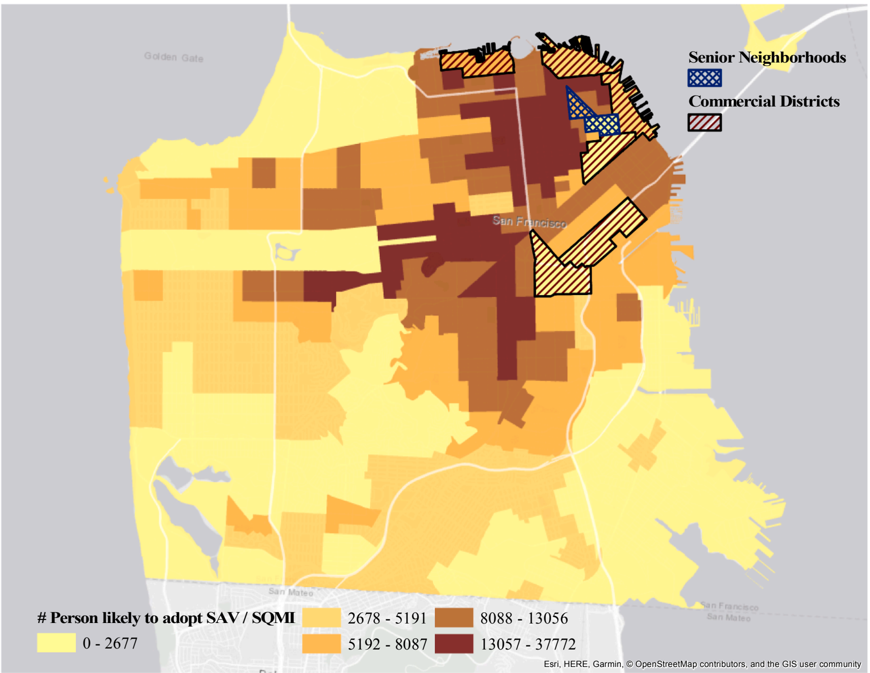
The marginal distributions of most predictive features are available in the ACS data, except for the frequency of ride-hailing behavior. However, the ride-hailing preference literature suggests that the likelihood to adopt this emerging travel mode is associated with income, race, ethnicity, age, gender, education, vehicle ownership, mode split, and family life cycle (Alemi et al., 2018; Bansal et al., 2019; Dias et al., 2017; Lavieri et al., 2018; Lavieri and Bhat, 2019). Thus, in this study, we controlled for the following household- and individual-level variables to generate a synthetic population at the Census Tract level:

- Household level: household income, vehicle ownership, and household size;
- Person level: age, gender, education attainment (age above 25), race, ethnicity, and commute mode (age above 16).

The generated synthetic population is then exported with the controlled household and individual variables as well as the imputed willingness to adopt PAVs and SAVs. The spatial distributions of PAV and SAV preferences are estimated by aggregating the synthesized population at the census tract level. In addition to AV preferences, we also included the ride-hailing frequency in the synthetic population output, which will be used to validate the proposed model framework.

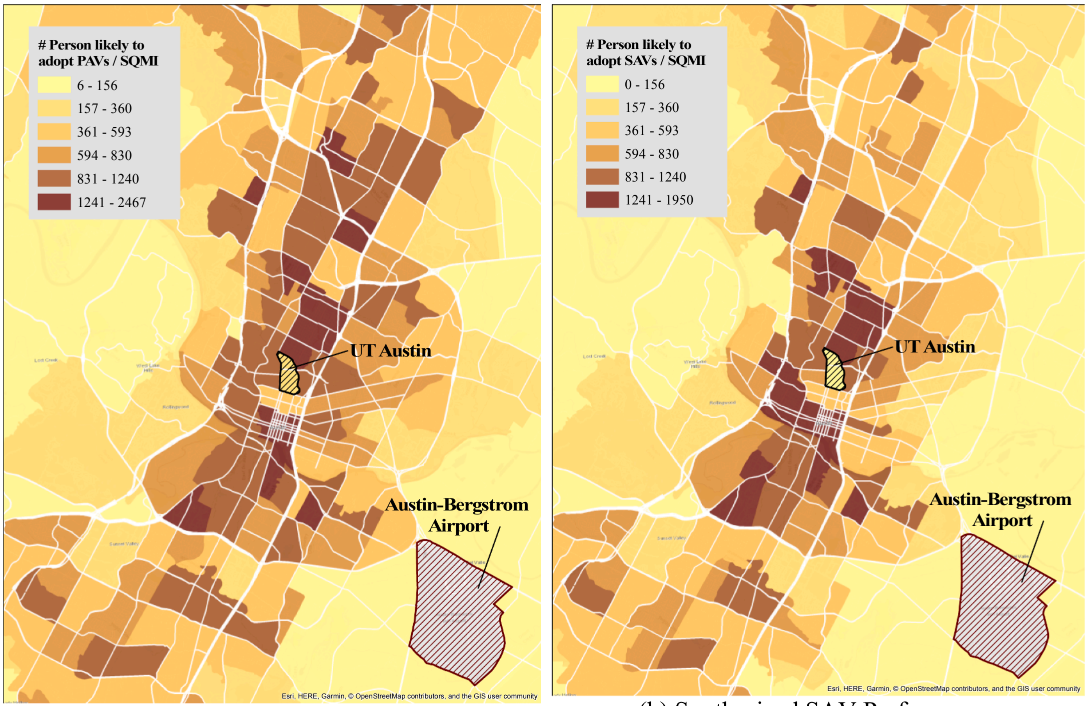


(a) Synthesized PAV Preferences



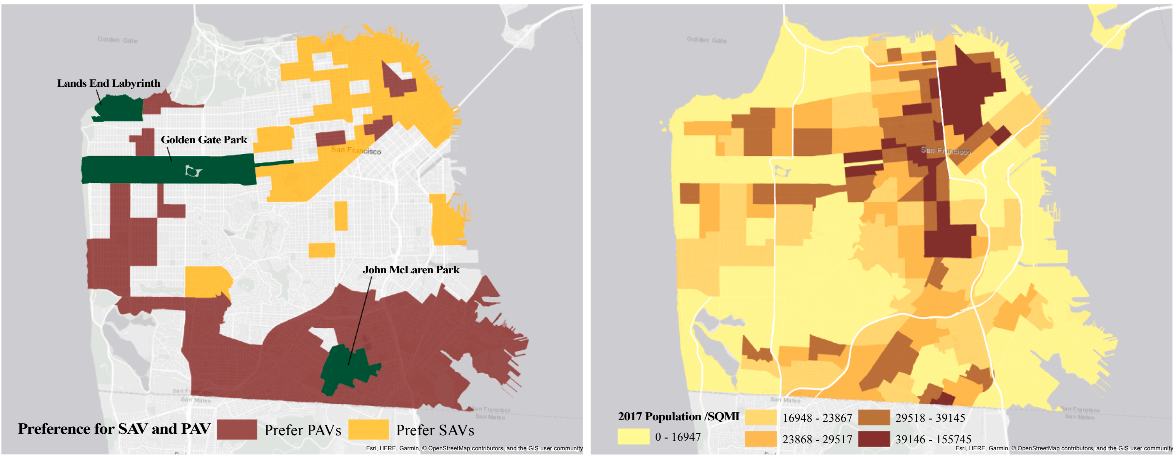
(b) Synthesized SAV Preferences

Fig. 3. San Francisco Synthesized PAV and SAV Adoption Density.



(a) Synthesized PAV Preferences (b) Synthesized SAV Preferences

Fig. 4. Austin Synthetic PAV and SAV Adoption Density.



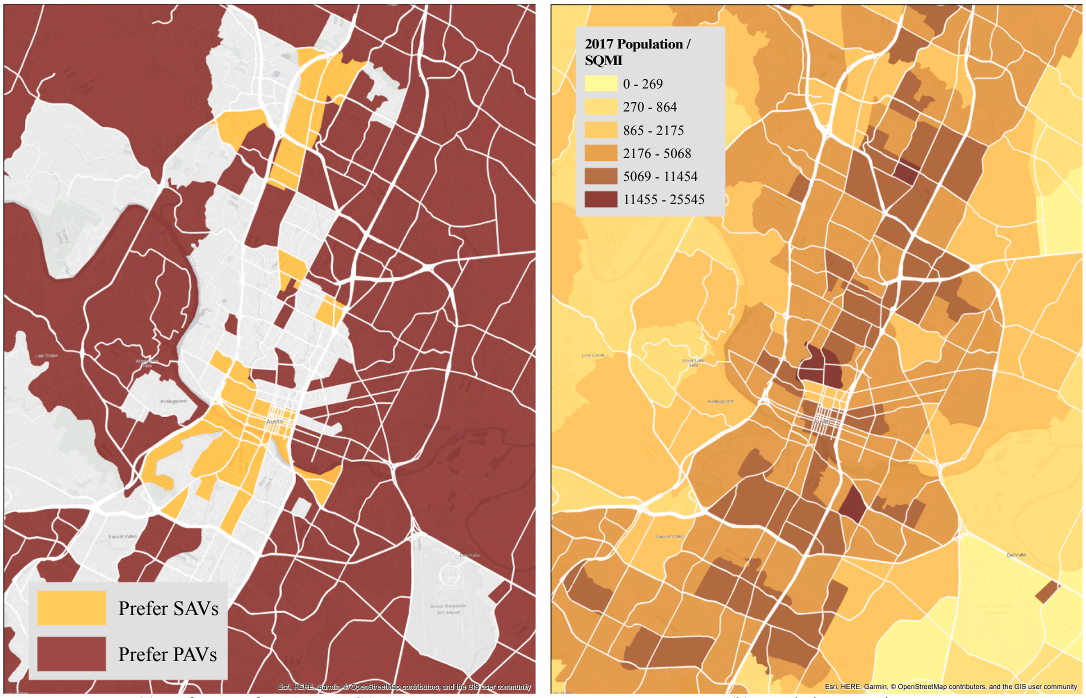
(a) Preferences for PAVs vs. SAVs (b) Population Density

Fig. 5. AV Preferences and Population Density in San Francisco, CA.

5. Results and discussion

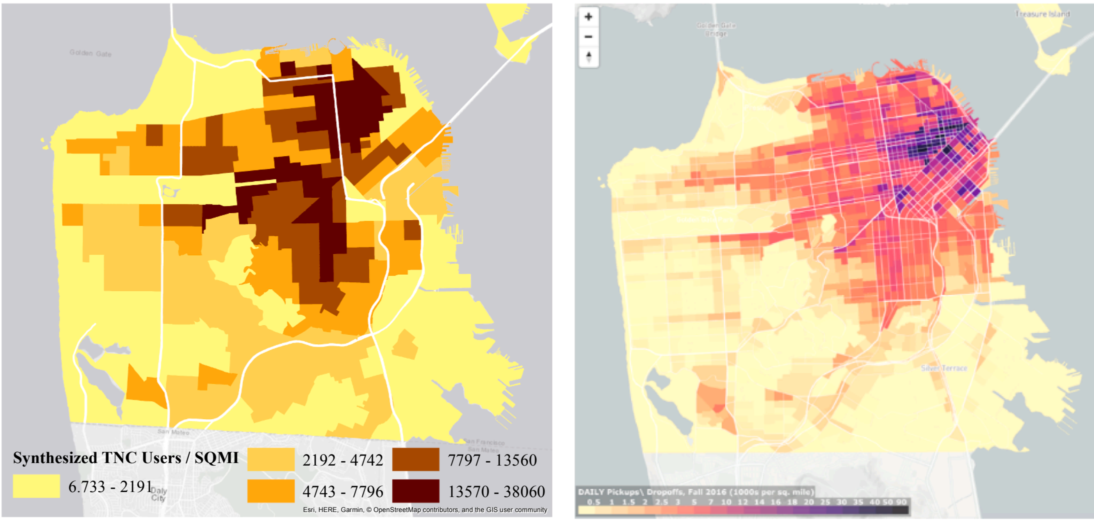
Fig. 3 shows the synthesized PAV and SAV adopters per square mile in San Francisco, CA. The results suggest that the preference for PAVs and SAVs are highly correlated, i.e., people who are willing to use AVs may show interest in both PAVs and SAVs. The San Francisco results show that the density of PAV and SAV adopters are generally lower in suburban neighborhoods and in commercial zones (i.e., the black dashed areas in Fig. 3a and b) where the population density is comparatively lower. Additionally, senior neighborhoods in Fig. 3b have 24% and 27% of 65+ population (the city average is 15%) and are less likely to adopt SAVs, which aligns with prior SAV preference survey results (Haboucha et al., 2017; Krueger et al., 2016; Wang et al., 2020).

The density of PAV and SAV adopters for Austin, TX are displayed in Fig. 4. Note that the density of early adopters at Austin-



(a) Preferences for PAVs vs. SAVs (b) Population Denstiy

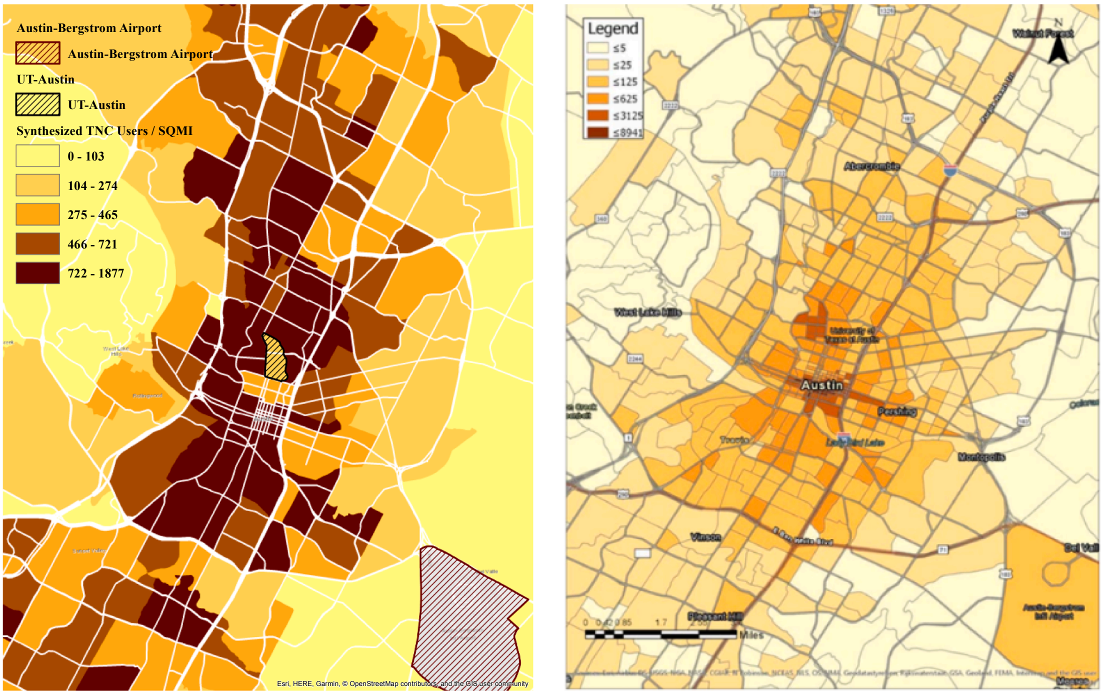
Fig. 6. AV Preferences and Population Density in Austin, TX.



(a) Synthesized Ride-hailing Users Density (b) Observed Ride-hailing Trip Density (Castiglione et al., 2016)

Fig. 7. Synthesized Ride-hailing Users and Trip Density in San Francisco.

Bergstrom International Airport (in the southeast corner) is zero, as there is no residential population in the census tract according to the ACS data. The density of synthesized adopters is also low around the University of Texas, Austin area (i.e., the black dashed area in the center), because students living in residence halls are not synthesized, as the NHTS data do not include this population. Similar to the synthesized results for San Francisco, the spatial distributions of the PAV and SAV adopters in Austin also tend to follow the same general trend. For both study areas, AV adoption rate maps are also developed and included in the Appendix for reference. In general, the pattern is quite similar to the adoption density maps; residents in urban areas are more likely to adopt AV technology. The adoption



(a) Synthesized Ride-hailing Users Density

(b) Observed Ride-hailing Trip Density (Nair et al., 2019)

Fig. 8. Synthesized Ride-hailing Users and Trip Density in Austin.

rate maps, however, can be misleading in areas with small population counts, such as rural, urban open space, commercial, and industrial tracts.

The synthesized results suggest that residents from suburban neighborhoods are more likely to adopt PAVs than SAVs. Figs. 5a and 6a show the difference between PAV and SAV adoption preferences by Census tract in both study areas. The red areas are Census Tracts, where the synthesized number of PAV adopters is 10% more than the SAV adopters, and the yellow areas indicate places where there are 10% more synthesized SAV adopters. The results indicate that suburban residents may prefer to use PAVs, while residents in urban cores or high-density areas are more likely to consider SAVs. Such results are consistent with the existing SAV preference surveys (Gkartzonikas and Gkritza, 2019).

We validated our model results by comparing the density of synthesized ride-hailing users with the density of ride-hailing trips in the two study areas. Fig. 7 shows a comparison for the San Francisco study area. The observed ride-hailing distribution is developed by the San Francisco County Transportation Authority (SFCTA) and published online (Castiglione et al., 2016). The screenshot in Fig. 7b shows the average trip pick-up density on Mondays at the Traffic Analysis Zone (TAZ) level. The spatial patterns of ride-hailing trips vary only slightly by day of the week. The distributions of the synthesized users and trip generation follow the same trend, except for the commercial zones, such as North Beach, the financial district, and along Market Street. The density of ride-hailing users in commercial zones is lower than the density of ride-hailing trips (in terms of ranking in the city) because the residential population in these zones is much smaller. In these zones, the ride-hailing trips may be produced or attracted by employment or points of interest rather than residents.

Fig. 8a and b displays the synthesized ride-hailing user density and the observed trip density in Austin, TX, separately. The observed ride-hailing trip density is visualized using the aggregated Ride Austin data by Nair et al. (2019). The spatial patterns for the two datasets are also quite comparable, except for the Airport, downtown areas, and UT Austin areas. Fewer residents in suburban areas tend to use ride-hailing Apps. Additionally, we found that the proposed method is transferable across cities. The synthesized percent of ride-hailing service users in Austin and San Francisco is 9.5% and 25.7%, respectively. The percent of observed ride-hailing users (weighted) at the Austin and San Francisco CBSA level according to 2017 NHTS data are 11.2% and 26.5%. This suggests that the model can potentially be applied to markets with different attitudes towards emerging transportation modes.

6. Conclusions

In this paper, we develop a transferrable methodology to impute preferences towards AVs across different geographic units in metropolitan areas. Most existing AV simulation studies are oversimplified by assuming homogenous adoption of AV technology in the study area, although current AV adoption studies suggest there is considerable heterogeneity in the preferences towards these emerging transportation technologies. The limitation of existing AV simulation studies stems from the fact that there is limited neighborhood-level AV preference data. In addition, the existing AV adoption models are difficult to transfer because they include variables that are not included in conventional travel demand surveys, such as attitudes and opinion variables.

We propose a machine learning-based microsimulation model to synthesize neighborhood-level preference towards PAVs and SAVs. The model has three steps to facilitate the estimation of AV preferences across geographic units. The first step is to train transferrable machine learning models for adults' preferences towards PAVs and SAVs using common socioeconomic, demographic, and built environment variables from representative NAVPS data. The trained PAV and SAV adoption models are highly predictive, with overall accuracy at approximately 80%. In the second step, the best-trained machine learning model is applied to NHTS or local travel survey data with common variables to impute AV adoption preferences for a sample of the local adult population. Finally, a population synthesizer is incorporated into the model to generate synthetic populations with different AV preferences across selected geographic units. The model proposed in this study is practical and transferrable, as it uses publicly available models (the trained machine learning PAV and SAV models are open-sourced on Github [https://github.com/nacici/AV-preference-synthesizing]), transportation datasets (e.g., NHTS (U.S. DOT and FHA, 2019) and local travel surveys), and population synthesizer (i.e., PopGen (Konduri et al., 2016)). The output data products can be easily integrated with existing agent-based AV simulations to generate agents with different AV preferences.

The proposed modeling approach is applied to the San Francisco, CA, and Austin, TX areas to test the concept. The model results are validated using two methods: (1) synthesized PAV and SAV adoption pattern analysis and (2) synthesized ride-hailing adoption density analysis. The model output results are consistent with the existing AV adoption literature, indicating the robustness of the proposed method. In general, the synthesized PAV and SAV adoption is higher in urban areas, except for zones where there is a low residential population (e.g., open space, commercial, and industrial zones), and the adoption is lower in senior neighborhoods. Additionally, the synthesizing results also suggest that urban residents are more likely to adopt SAVs, while suburban residents may prefer PAVs, which is consistent with AV adoption studies. Finally, the synthesized ride-hailing adoption pattern is also consistent with the existing TNC trip generations. The model can accurately recreate the overall adoption of ride-hailing services using the common demographic and socioeconomic variables for cities with significantly different levels of adoption rates. The synthesized ride-hailing adoption rates in San Francisco and Austin are 25.7% and 9.5% (compared with 26.5% and 11.2% from NHTS).

The contributions of this work can be extended to gain a deeper understanding of neighborhood-AV preferences. First, the proposed model framework can benefit from additional national AV preference surveys with more refined built environment and transportation infrastructure availability data, as well as using NHTS data with more refined geographic information, which are only available upon request. The methodology introduced here can address claims that the adoption of emerging transportation technologies can be influenced by the built environment, such as existing transportation infrastructure and walkability. In this study, we test limited built environment variables, such as population and employment density, but find them not to be predictive. Second, like many existing AV preference surveys, the NAVPS was conducted at the individual level, while prior studies suggest that household vehicle ownership and travel patterns can vary by household structure and is typically a household-level decision. Thus, the existing model can be advanced by replacing the individual-level AV adoption machine learning model, with more advanced multi-level (i.e., household and individual level) models. Third, the current model is only validated using samples from cities with medium to high ride-hailing adoption rates. More empirical studies should be conducted to validate the applicability of the proposed model outside of CBSA areas in small cities and rural areas. Finally, we recognize that there are substantial uncertainties embedded in the deployment of AV technology and the adoption pattern may evolve based on the final design, operation constraints, and commercial deployment of AVs (Leonard et al., 2020). Future studies are needed once the technology becomes more mature for real-world implementation.

Declaration of Competing Interest

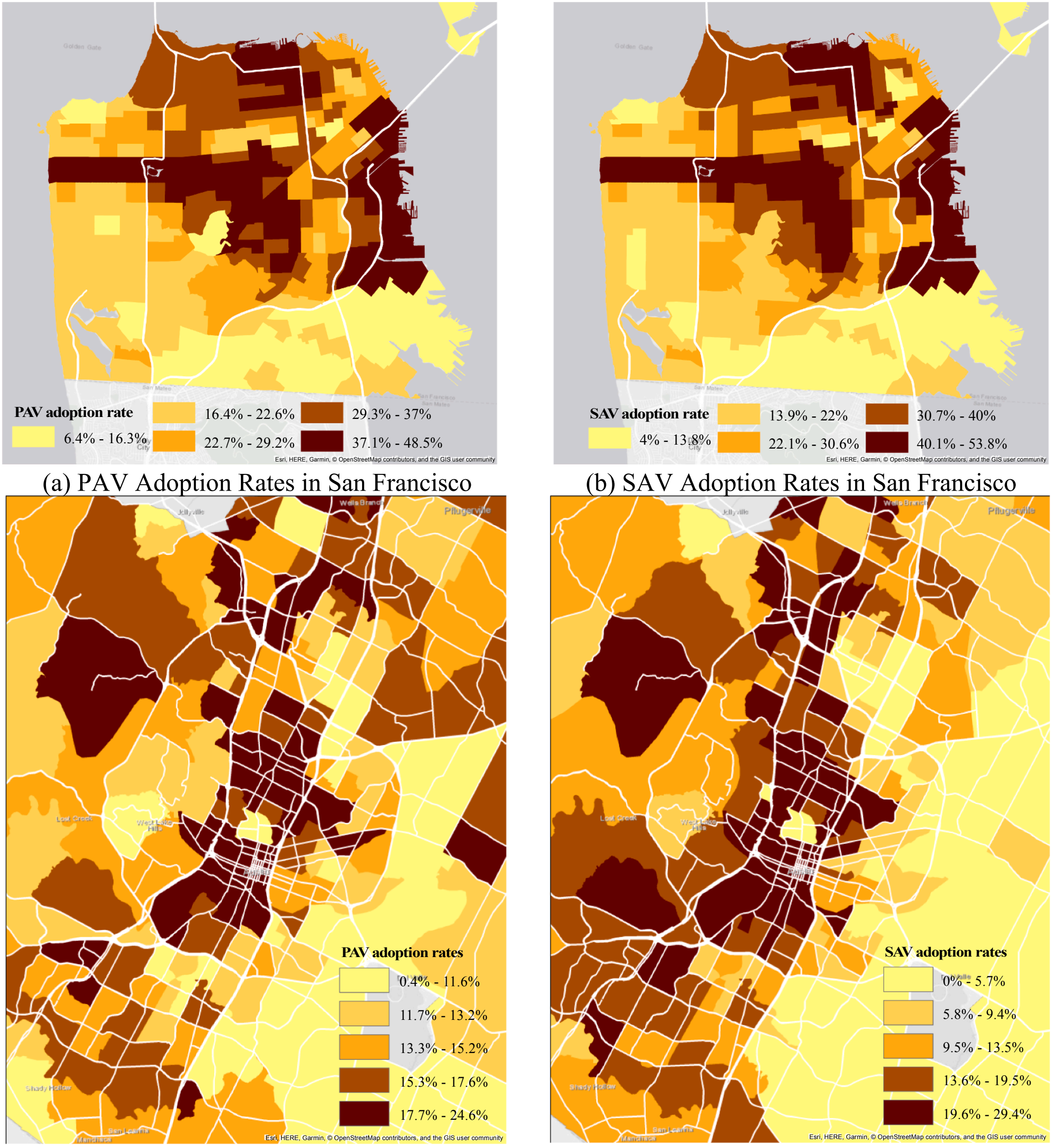
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Authors would like to thank 4-VA Collaborative Research Grant for partial support of this research. We also appreciate the comments and suggestions provided by the three anonymous reviewers, which significantly improved this manuscript.

Appendix A

See Fig. 9 and Tables 3 and 4.



(a) PAV Adoption Rates in San Francisco (b) SAV Adoption Rates in San Francisco

(c) PAV Adoption Rates in Austin (d) SAV Adoption Rates in Austin

Fig. 9. PAV and SAV Adoption Rates in San Francisco and Austin (classfied by quantile method).

Table 3
Machine Learning Hyperparameters Tuning Summary.

Model	Parameter Name in Scikit-learn Package	Test Range
Decision Tree Classifier	max_features	[5, 30]
	max_depth	[1, 10]
	min_samples_split	[2, 30]
	min_samples_leaf	[1, 20]
Extra Tree Classifier	max_features	[5, 30]
	max_depth	[1, 10]
	min_samples_split	[2, 30]
	min_samples_leaf	[1, 20]
KNeighbors Classifier	n_neighbors	[1, 20]
	p	[1, 3]
SVC	kernel	['linear', 'rbf', 'poly']
	gamma	[0.1, 1, 10]
	C	[0.1, 1, 10, 100]
	degree	[0, 3]
Ridge	alpha	[0.01, 0.1, 1, 10]
Logistic Regression	alpha	[0.01, 0.1, 1, 10]
Random Forest Classifier	n_estimators	[10, 100]
	max_features	[5, 30]
	max_depth	[1, 10]
	min_samples_split	[2, 30]
	min_samples_leaf	[1, 20]
Gradient Boosting Classifier	n_estimators	[10, 100]
	max_features	[5, 30]
	max_depth	[1, 10]
	min_samples_split	[2, 30]
	min_samples_leaf	[1, 20]

Table 4
Common Variables in NAVPS and NHTS data.

Common Variables	FAV Natioal Survey	NHTS	Recoding
Gender	Female, Male	Female, Male	Female; Male
Hispanic	Yes, No	Yes, No	Yes; No
Race	White, African American, Asian, Other	White, African American Asian, Other	White, African American Asian, Other
Age	Numeric	Numeric	Numeric
Generation	Millennials, Generation X, Baby Boomers, The Silent Generation	Imputed	Millennials, Generation X, Baby Boomers, The Silent Generation
Rideshare	Never, A few times per year, Once per month, Once per week, Several times per week	Numeric, # of times using ridesharing app in the past 30 days	Never or A few times/year (0) Once per month (1–2) Once per week (3–6) Several times/week (>6)
Commute Mode	Personal Automobiles, Biking or Walking, Public Transit, Taxi Uber or Lyft, Other	Personal Automobiles, Biking or Walking, Public Transit, Taxi Uber or Lyft, … Other	Personal Automobiles, Biking or Walking, Public Transit, Taxi Uber or Lyft, Other
Education	Less than high school, High school of GED, Some College, Two-year College, Four-year College, Master or above	Less than high school, High school of GED, Some College, Bachelor, Master or above	Less than high school, High school of GED, Some College, Bachelor, Master or above
Vehicle Count	0, 1, 2, 3, 4, 5, 6+	Numeric	0, 1, 2, 3, 4, 5, 6+
Household Size	0, 1, 2, 3, 4, 5, 6+	Numeric	0, 1, 2, 3, 4, 5, 6+
# of children (<18)	0, 1, 2, 3, 4+	Imputed	0, 1, 2, 3, 4+
Family Income	Under $25, 000, $25,000–$49, 999 $50, 000–$99,999 $100,000–$149,999 $150,000–$199,999 $200,000 +	Less than $10,000 $10,000–$14,999 $15,000–$24,999 … $200,000 or more	Under $25,000, $25,000–$49,999 $50,000–$99,999 $100,000–$149,999 $150,000–$199,999 $200,000 +
Built Enviornment Variables	Zipcode	State, CBSA, Population and Employment Densities (per square mile)	State dummies, Regional Dummies, Population and employment densities (per square mile) at home location

References

Abraham, H., Lee, C., Brady, S., Fitzgerald, C., Mehler, B., Reimer, B., Coughlin, J.F., 2016. Autonomous Vehicles, Trust, and Driving Alternatives: A Survey of Consumer Preferences. Massachusetts Inst. Technol, AgeLab, Cambridge, pp. 1–16.

Alemi, F., Circella, G., Handy, S., Mokhtarian, P., 2018. What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. Travel Behav. Soc. 13, 88–104.

Asgari, H., Jin, X., Corkery, T., 2018. A stated preference survey approach to understanding mobility choices in light of shared mobility services and automated vehicle technologies in the US. Transp. Res. Rec. 2672 (47), 12–22.

Bansal, P., Kockelman, K.M., 2017. Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. Transp. Res. Part A: Policy Pract. 95, 49–63.

Bansal, P., Kockelman, K.M., 2018. Are we ready to embrace connected and self-driving vehicles? A case study of Texans. Transportation 45 (2), 641–675.

Bansal, P., Sinha, A., Dua, R., Daziano, R., 2019. Eliciting preferences of ridehailing users and drivers: Evidence from the United States. ArXiv Preprint ArXiv: 1904.06695.

Begg, D., 2014. A 2050 Vision for London: What are the implications of driverless transport?.

Bösch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. Transp. Policy 64, 76–91.
Breiman, L., 2001. Random forests. Mach. Learn. 45 (1), 5–32.
Brown, B., Drew, M., Erenguc, C., Hasegawa, M., Hill, R., Schmith, S., Ganula, B., 2014. Global Automotive Consumer Study: The Changing Nature of Mobility—Exploring Consumer Preferences in Key Markets around the World. Technical Report, Deloitte. Retrieved from: https://www2.deloitte.com.
Burns, L.D., Jordan, W.C., Scarborough, B.A., 2013. Transforming Personal Mobility. Earth Island Institute, Columbia University.
Castiglione, J., Chang, T., Cooper, D., Hobson, J., Logan, W., Young, E., Charlton, B., Wilson, C., Mislove, A., Chen, L., et al., 2016. TNCs today: A Profile of San Francisco Transportation Network Company Activity. San Francisco County Transportation Authority.
Chen, T.D., Kockelman, K.M., Hanna, J.P., 2016. Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. Transp. Res. Part A: Policy Pract. 94, 243–254. https://doi.org/10.1016/j.tra.2016.08.020.
Choi, J.K., Ji, Y.G., 2015. Investigating the importance of trust on adopting an autonomous vehicle. Int. J. Hum.-Comput. Interact. 31 (10), 692–702.
Dias, F.F., Lavieri, P.S., Garikapati, V.M., Astroza, S., Pendyala, R.M., Bhat, C.R., 2017. A behavioral choice model of the use of car-sharing and ride-sourcing services. Transportation 44 (6), 1307–1323.
Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. Transp. Res. Part A: Policy Pract. 77, 167–181. https://doi.org/10.1016/j.tra.2015.04.003.
Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transp. Res. Part C: Emerg. Technol. 40, 1–13. https://doi.org/10.1016/j.trc.2013.12.001.
Fagnant, D.J., Kockelman, K.M., 2018. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Transportation 45 (1), 143–158. https://doi.org/10.1007/s11116-016-9729-z.
Friedman, J.H., 2002. Stochastic gradient boosting. Comput. Stat. Data Anal. 38 (4), 367–378.
Geurts, P., Ernst, D., Wehenkel, L., 2006. Extremely randomized trees. Mach. Learn. 63 (1), 3–42.
Gkartzonikas, C., Gkritza, K., 2019. What have we learned? A review of stated preference and choice studies on autonomous vehicles. Transp. Res. Part C: Emerg. Technol. 98, 323–337.
Greenblatt, J.B., Saxena, S., 2015. Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. Nat. Clim. Change 5 (9), 860.
Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. Transp. Res. Part C: Emerg. Technol. 78, 37–49.
Harper, C.D., Hendrickson, C.T., Constantine, S., 2018. Exploring the economic, environmental, and travel implications of changes in parking choices due to driverless vehicles: An agent-based simulation approach. J. Urban Plann. Dev. 144 (4), 04018043. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000488.
Hassan, H.M., Ferguson, M.R., Razavi, S., Vrkljan, B., 2019. Factors that influence older canadians' preferences for using autonomous vehicle technology: A structural equation analysis. Transp. Res. Rec. 2673 (1), 469–480.
Hoerl, A.E., Kennard, R.W., 1970. Ridge regression: Biased estimation for nonorthogonal problems. Technometrics 12 (1), 55–67.
Howard, D., Dai, D., 2014. Public perceptions of self-driving cars: The case of Berkeley, California. In: Transportation Research Board 93rd Annual Meeting, 14, pp. 1–16.
Ipsos, M., 2014. Ipsos MORI Loyalty Automotive Survey. Technical Report. 26.
Jiang, Z., Wang, S., Mondschein, A.S., Noland, R.B., 2020. Spatial distributions of attitudes and preferences towards autonomous vehicles. Transp. Find. https://doi.org/10.32866/001c.12653.
Keller, J.M., Gray, M.R., Givens, J.A., 1985. A fuzzy k-nearest neighbor algorithm. IEEE Trans. Syst. Man Cybern. 4, 580–585.
Kondor, D., Santi, P., Basak, K., Zhang, X., Ratti, C., 2018. Large-scale estimation of parking requirements for autonomous mobility on demand systems. ArXiv Preprint ArXiv:1808.05935.
Konduri, K.C., You, D., Garikapati, V.M., Pendyala, R.M., 2016. Application of an enhanced population synthesis model that accommodates controls at multiple geographic resolutions. Transp. Res. Rec., J. Transp. Res. Board 2563, 40–50.
Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transp. Res. Part C: Emerg. Technol. 69, 343–355.
Kyriakidis, M., Happee, R., de Winter, J.C., 2015. Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. Transp. Res. Part F: Traff. Psychol. Behav. 32, 127–140.
Lavieri, P.S., Bhat, C.R., 2019. Investigating objective and subjective factors influencing the adoption, frequency, and characteristics of ride-hailing trips. Transp. Res. Part C: Emerg. Technol. 105, 100–125.
Lavieri, P.S., Dias, F.F., Juri, N.R., Kuhr, J., Bhat, C.R., 2018. A model of ridesourcing demand generation and distribution. Transp. Res. Rec. 0361198118756628.
Lavieri, P.S., Garikapati, V.M., Bhat, C.R., Pendyala, R.M., Astroza, S., Dias, F.F., 2017. Modeling individual preferences for ownership and sharing of autonomous vehicle technologies. Transp. Res. Rec. 2665 (1), 1–10.
Leonard, J.J., Mindell, D.A., Stayton, E.L., 2020. Autonomous vehicles, mobility, and employment policy: The roads ahead (p. 34). https://workofthefuture.mit.edu/sites/default/files/2020-07/WotF-2020-Research-Brief-Leonard-Mindell-Stayton.pdf.
Martinez, L., Crist, P., 2015. Urban mobility system upgrade–How shared self-driving cars could change city traffic. https://www.itf-oecd.org/urban-mobility-system-upgrade-1.
Milakis, D., van Arem, B., van Wee, B., 2017. Policy and society related implications of automated driving: A review of literature and directions for future research. J. Intell. Transp. Syst. 21 (4), 324–348. https://doi.org/10.1080/15472450.2017.1291351.
Nair, G.S., Bhat, C.R., Batur, I., Pendyala, R.M., Lam, W.H., 2019. A model of deadheading trips and pick-up locations for ride-hailing service vehicles.
Payre, W., Cestac, J., Delhomme, P., 2014. Intention to use a fully automated car: Attitudes and a priori acceptability. Transp. Res. Part F: Traff. Psychol. Behav. 27, 252–263.
Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., et al., 2011. Scikit-learn: Machine learning in Python. J. Mach. Learn. Res. 12 (Oct), 2825–2830.
Platt, J., et al., 1999. Probabilistic outputs for support vector machines and comparisons to regularized likelihood methods. Adv. Large Margin Classif. 10 (3), 61–74.
Power, J. et al., 2012. Vehicle owners show willingness to spend on automotive infotainment features. Retrieved July, 24, 2017.
Power, J. et al., 2013. Automotive emerging technologies study results. Retrieved July, 24, 2017.
Schoettle, B., Sivak, M., 2014a. A Survey of Public Opinion about Autonomous and Self-driving Vehicles in the US, the UK, and Australia. University of Michigan, Ann Arbor, Transportation Research Institute.
Schoettle, B., Sivak, M., 2014b. Public Opinion about Self-driving Vehicles in China, India, Japan, the US, the UK, and Australia. University of Michigan, Ann Arbor, Transportation Research Institute.
Shin, J., Bhat, C.R., You, D., Garikapati, V.M., Pendyala, R.M., 2015. Consumer preferences and willingness to pay for advanced vehicle technology options and fuel types. Transp. Res. Part C: Emerg. Technol. 60, 511–524.
Spurlock, C.A., Sears, J., Wong-Parodi, G., Walker, V., Jin, L., Taylor, M., Duvall, A., Gopal, A., Todd, A., 2019. Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area. Transp. Res. Part D: Transp. Environ. 71, 283–301.
Swain, P.H., Hauska, H., 1977. The decision tree classifier: Design and potential. IEEE Trans. Geosci. Electron. 15 (3), 142–147.
Taiebat, M., Brown, A.L., Safford, H.R., Qu, S., Xu, M., 2018. A review on energy, environmental, and sustainability implications of connected and automated vehicles. Environ. Sci. Technol. 52 (20), 11449–11465.
U.S. Department of Transportation, & Federal Highway Administration, 2019. 2019 National Household Travel Survey. https://nhts.ornl.gov.
Vallet, M., 2013. Survey: Drivers ready to trust robot cars. CarInsurance.Com.
Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transp. Res. Part A: Policy Pract. 86, 1–18.
Wang, K., Xie, W., Zhang, W., 2019. Parking space optimization in the era of private automated vehicles. Transportation Research Board 98th Annual Meeting.
Wang, K., Akar, G., 2019. Factors affecting the adoption of autonomous vehicles for commute trips: An analysis with the 2015 and 2017 Puget sound travel surveys. Transp. Res. Rec. 2673 (2), 13–25.

Wang, S., Jiang, Z., Noland, R.B., Mondschein, A.S., 2018. Self-driving cars survey questionnaire. Accessed at https://doi.org/10.7282/t3-9d68-0k53.
Wang, S., Jiang, Z., Noland, R.B., Mondschein, A.S., 2020. Attitudes towards privately-owned and shared autonomous vehicles. Transp. Res. Part F: Traff. Psychol. Behav. 72, 297–306. https://doi.org/10.1016/j.trf.2020.05.014.
Zhang, W., Guhathakurta, S., 2017. Parking spaces in the age of shared autonomous vehicles: How much parking will we need and where? Transp. Res. Rec.: J. Transp. Res. Board 2651, 80–91.
Zhang, W., Guhathakurta, S., 2018a. The impact of private autonomous vehicles on vehicle ownership and unoccupied VMT generation. Transp. Res. Part C: Emerg. Technol. 90, 156–165. https://doi.org/10.1016/j.trc.2018.03.005.
Zhang, W., Guhathakurta, S., 2018b. Residential location choice in the era of shared autonomous vehicles, residential location choice in the era of shared autonomous vehicles. J. Plan. Educ. Res. https://doi.org/10.1177/0739456X18776062, 0739456X18776062.
Zhang, W., Guhathakurta, S., Fang, J., Zhang, G., 2015a. The performance and benefits of a shared autonomous vehicles based dynamic ridesharing system: An agent-based simulation approach. Transportation Research Board 94th Annual Meeting Proceeding.
Zhang, W., Guhathakurta, S., Fang, J., Zhang, G., 2015b. Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. Sustain. Cities Soc. 19, 34–45. https://doi.org/10.1016/j.scs.2015.07.006.
Zhang, W., Wang, K., 2020. Parking futures: Shared automated vehicles and parking demand reduction trajectories in Atlanta. Land Use Policy 91, 103963. https://doi.org/10.1016/j.landusepol.2019.04.024.
Zmud, J.P., Sener, I.N., 2017. Towards an understanding of the travel behavior impact of autonomous vehicles. Transp. Res. Procedia 25, 2500–2519.