BUILT ENVIRONMENT AND AUTONOMOUS VEHICLE MODE CHOICE: A FIRST-MILE SCENARIO IN SINGAPORE

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ABSTRACT

This study investigates travel mode choice with on-demand autonomous vehicle (AV). It takes Singapore as the study area and specifically focuses on understanding the impacts of built environment (BE) on first-mile scenarios. A dynamic stated preference survey is developed to automatically generate first-mile travel scenarios based on the respondent's dwelling location and real-world traffic information. Two mixed logit models with panel data structures are adopted to explore the impacts of BE on AV mode choice. The results reveal that BE factor is independent of trip specific and sociodemographic variables. Although including BE does not significantly improve the model fitting, it adds to explain the nuances of individual's preference on travel mode choice. We then employ the models to forecast AV mode choice of 11,545 individuals from the Household Interview Travel Survey of Singapore. It provides a good understanding of AV market share in different areas and helps in evaluating the planning for AV deployment in Singapore. The estimation shows the mode shares of AV in most of pilot areas with AV plans are quite low. Thus, revisiting the planning of pilot areas for future AV deployment may be needed to avoid a spatial mismatch of on-demand AV service.

Keywords: Autonomous Vehicle, Built Environment, Dynamic Survey, First Mile, Travel Behavior

INTRODUCTION

The innovation of autonomous vehicles (AV), on-demand mobility and shareability, has the potential to reduce negative externalities of transportation system (*1; 2*). Some studies treat AVs as an upgrade of conventional private vehicles and find that the rebalancing of AVs may incur traffic congestions (*3-6*). However, in urban areas with high population density and limited land availability, the use of public transportation, instead of private vehicles, should be encouraged to mitigate traffic congestions. To promote public transit and to reduce car usage, enhancing first- and last-mile connection becomes a key challenge. Constrained accessibility to public transit may force traveler to choose a feeder service or even shift to private vehicle, leading to the decline of efficiency in urban mobility.

AV technology is promising to deliver automatous on-demand service with high share-ability which offers an innovation solution for the first- and last-mile connections (*7; 8*). It is thus essential to understand the choice behavior and preference on AVs especially for the first- and last-mile travels. However, current literature on AV user preference mainly focuses on public acceptance and adoption of AV as a commuting travel mode across the population. In general, people would rather own a private AV and are quite optimistic to the AVs in the future (*9-11*). Daziano et al. (*12)* conduct a nationwide survey in the U.S. and find that, on average, the households are willing to pay a significant amount for vehicle automation, but the demand for automation diversifies. Other common findings are that young individuals who are more educated and familiar with emerging technology are more preferable to use AVs (*13-16*). In addition to the trip specific attributes like travel cost of AV, the safety and liability of the AV technology, and convenience for automatic parking are the major concerns for AV adoption (*17; 18*). In terms of the future penetrations rates of AV in different countries, Kröger et al. (*19)* yield that the AV fleet size might be higher in Germany than that in the U.S. due to higher share of luxury cars and quicker fleet turnover. Despite of the fruitful findings on user preference of AVs for commuting trips, the studies on the preference of AV as a first- and last-mile travel mode are quite limited. A survey conducted by Yap et al. (*20)* shows that, the perception of time use in last mile connection using AV is more sensitive than that in conventional cars, which contradicts the theoretical advantage of multitasking in AV. It implies that, classical findings on user adoption on AVs as a commuting travel mode may not be directly applied to the first- and last-mile travel scenarios.

In addition, built environment (BE) variables are absent among the current studies on AV behaviors as well, despite of the general consensus among the literature that BE influences travel mode choice (*21-23*). Fraedrich et al. (*24)* explore the opportunities for AV to affect the BE from a planning perspective; but the discussion of how BE influences travel mode choice with AV still remains open. Mo et al. (*25)* find that BE significantly and heterogeneously impact the first- and last-mile travel behaviors. Nevertheless, in the study, on-demand AV service is not listed as an available travel mode alternative.

To fill the gap, this study investigates the impact of BE on AV travel model choice with a specific focus on the first-mile travel scenarios. We select Singapore as the study area, where public transit has a high share in daily travel. According to the Household Travel Interview Survey (HITS) conducted in 2012, 70% of commuters in the country go to work by public transit, including the metro (i.e. mass rapid transit, MRT) and bus. The phenomenon raises the importance of the first and last mile problem in Singapore. In addition, by 2022, the Land Transport Authority of Singapore plans to pilot the deployment of on-demand AV in several areas to enhance first- and last-mile connectivity (*26*). There are also some academic discussions regarding to implement the on-demand AV service in Toa Payoh (*27*) and in the Central Area (*28*).

The reminder of the paper is organized as follows. In the next section, a dynamic survey method incorporating spatial information is described. Section 3 presents the descriptive analysis of the collected data adopted for this research. In Section 4, two mixed logit models with panel data structures are developed to understand the first-mile modal choice behaviors with AV, taking account of the impacts of BE. In Section 5, we revisit the planning for AV deployment in Singapore and forecast the future first-mile mode share after the deployment of AV in different planning areas (PA). Finally, we conclude the study with some discussions.

SURVEY DESIGN

Traditional travel surveys are mostly static and independent of the geographical characteristics of survey participants. Static stated preference (SP) parameters may not realistically link to a respondent's daily trips or mode choices, leading to invalidity and bias in behavior estimation. In this study, we develop a dynamic web-based SP survey incorporating the first-mile scenarios generated from of the respondent's actual dwelling location, which allows us to capture the impact of BE on travel behaviors with AV. The specific design of survey is presented in Figure 1. The survey is coded in JavaScript integrating Google Maps API with two layers: the user interface at frontend for visualization of survey questions, and the data processor at backend to process spatial data in real time and to generate SP survey scenarios based on the location data.

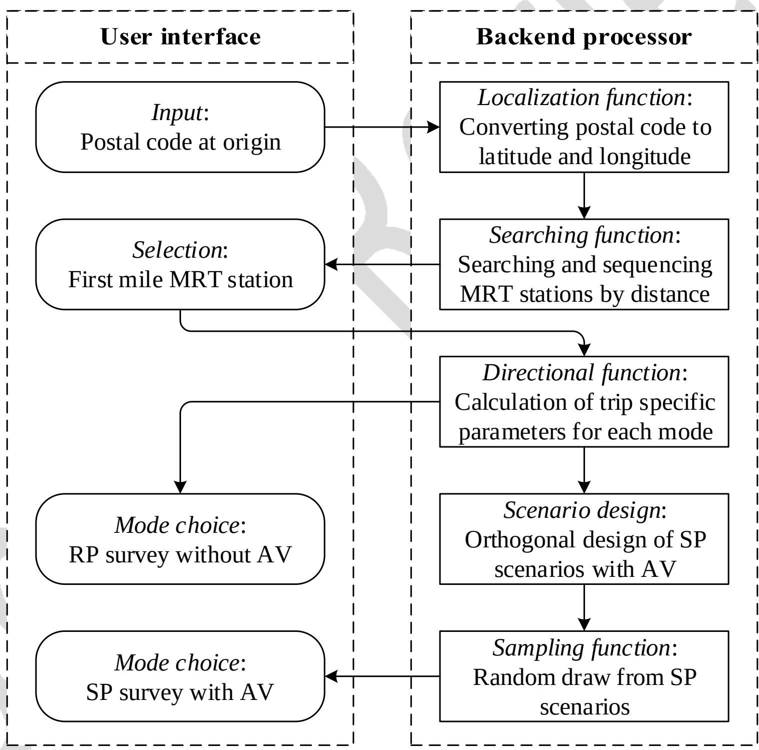

FIGURE 1 Design of survey

Postal code in Singapore accurately locates each building. Once the postal code is provided by a survey participant, the backend processor can automatically identify a set of candidate first-mile MRT stations close to the participant's dwelling location. After a station is selected, the processor calculates trip specific parameters including travel time and travel cost of each travel mode based on Google Maps. A revealed preference (RP) survey based on actual travel information without AV is presented to the participants. This design enables a joint estimation based on RP and SP, which potentially corrects the bias from pure SP survey and to keep the preference on new products or new attributes identifiable (*29*). In parallel with the frontend, the system generates the orthogonal SP scenarios based on the trip specific variables and randomly draws a sample of scenarios from the full orthogonal design for survey participants to response.

The visualization of the SP first-mile modal choice scenario is exemplified in Figure 2, with four available travel modes: walk, bus, ride hailing such as Uber/Grab or taxi, and the on-demand AV. In the choice set, the availability of bus depends on the suggestions from Google Maps trip planner: if there is no available bus service between the respondent's location and the chosen MRT station, bus travel mode is then removed from the choice set.

FIGURE 2 Example of choice set presented in the survey

A 1-minute introductive video is presented to the survey participants to explain the on-demand AV service before the SP survey. In addition, to help the survey respondents easily understand the on-demand AV, we use the alternative name of "ride hailing with AV" in the survey. Given the four alternatives, 11 trip specific variables, listed in Table 1, are designed for the experiments with 3 levels each. The medium level of bus travel cost is determined based on the base bus fare structure in Singapore during morning peak hours; the waiting time variables are designed empirically according to the waiting time distribution in the HITS data. The dynamic travel time variables are automatically generated by Google Maps, while the travel cost variables are calculated according to current Uber/Grab pricing schemes in Singapore.

TABLE 1 Attributes and attribute levels in the SP survey

Attributes	Attribute levels		
Static variables			
Bus: Travel cost	S$0.5	S$0.9	S$1.5
Bus: Waiting time	3 min	5 min	10 min
Ride hailing: Waiting time	1 min	3 min	8 min
On-demand AV: Waiting time	1 min	3 min	8 min
Dynamic variables			
Walk: Walking time	$WT_{walk}\times0.5$	WT_{walk}	$WT_{walk}\times1.5$
Bus: Walking time	$WT_{bus}\times0.5$	WT_{bus}	$WT_{bus}\times1.5$
Bus: In-vehicle time	$IVT_{bus}\times0.5$	IVT_{bus}	$IVT_{bus}\times1.5$
Ride hailing: Travel cost	$C_{hailing}\times0.5$	$C_{hailing}$	$C_{hailing}\times1.5$
Ride hailing: In-vehicle time	$IVT_{hailing}\times0.5$	$IVT_{hailing}$	$IVT_{hailing}\times1.5$
On-demand AV: Travel cost	$C_{AV}\times0.2$	C_{AV}	$C_{AV}\times2.0$
On-demand AV: In-vehicle time	$IVT_{AV}\times0.2$	IVT_{AV}	$IVT_{AV}\times2.0$

DATA COLLECTION

The survey was implemented using Qualtrics online survey platform during June and July in 2017, with 1,242 valid samples collected. The locations of survey respondents are drawn in Figure 3 to exhibit the spatial representativeness of samples. The samples cover the main residential areas in the country, and the spatial distribution is consistent with that of the whole population. According to the generated RP survey without on-demand AV, the choice of first-mile MRT station and mode choice are also illustrated. In general, walk and bus are still the dominant travel modes for the first-mile travel. However, comparing with the first-mile mode choice in 2012 presented by Mo et al. (*25)*, more people start to choose ride hailing service like Uber/Grab for first mile connections.

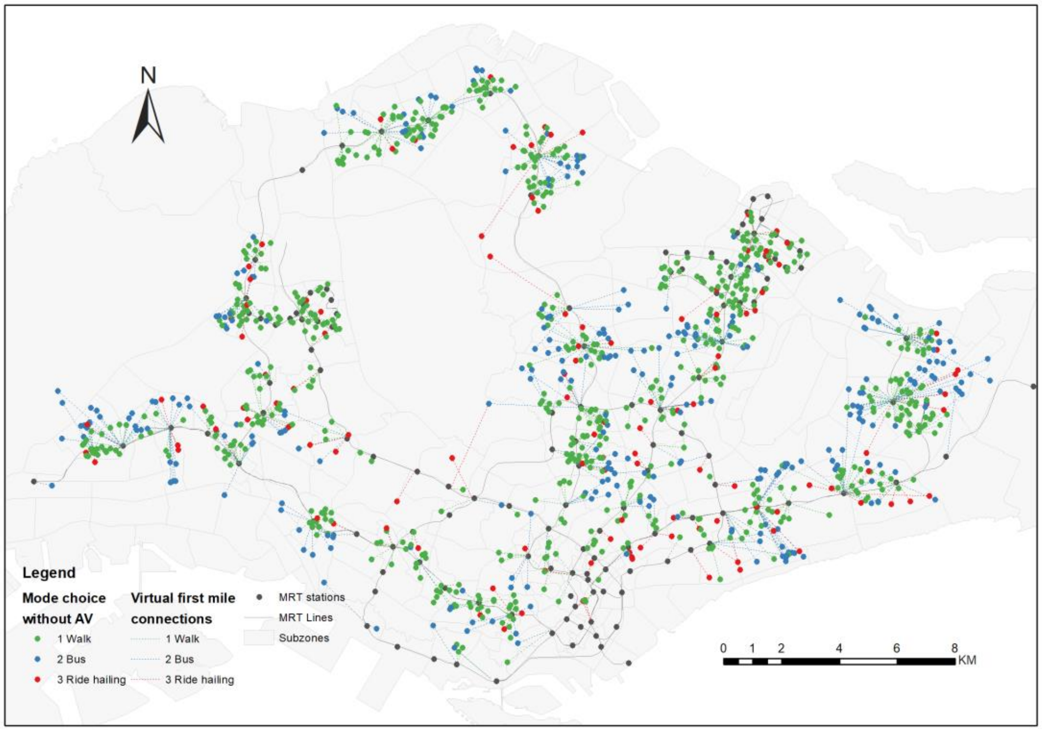

FIGURE 3 Spatial representativeness of survey samples

Sociodemographic Information

The detailed sociodemographic statistics of survey participants are listed in Table 2. The data include age, gender, education level, employment status, and household income. The information of age and household income are used to control the sample representativeness in the beginning of the survey, which are thus complete for all respondents. Other sociodemographic survey questions are optional, where 336 respondents choose not to report their employment status and education levels; and 338 refuse to report their genders.

TABLE 2 Sociodemographic information

Attributes	Categories and summary			
Gender	*Male*	*Female*	*Unknown*	
	420	484	338	
Age	*Below 25*	*26 to 45*	*46 to 65*	*Over 66*
	187	657	359	39
Education level	*Postgraduate*	*Graduate*	*Undergraduate*	*Unknown*
	95	426	385	336
Employment status	*Full employment*	*Other employment status*	*Unknown*	
	622	284	336	
Household income	*Below S$4,000*	*S$4,000 to S$12,000*	*Over S$12,000*	
	505	507	230	

Built Environment

To examine the relationship between the BE and travel behavior, various elements of the BE need to be appropriately measured at certain geographical scale. This study focuses on measuring land use and transportation infrastructure at the level of traffic analysis zone (TAZ).

Floor area ratio (FAR) is computed for residential, commercial and industrial buildings. The metric approximates the density of population and employment. Residential buildings are categorized into public and private housing. In Singapore, over 80% of population live in public residence and the government has strict regulations on resale and rent of public housing.

Density and diversity are also quantified using the POIs from Google Maps. We classify the POIs following Shen et al. (*30)*. The density is calculated as the number of POIs per km^2, and its diversity is characterized using the Shannon entropy showing the mixture of activities in each TAZ:

$$H(X) = -\sum_i p(i) \log_c p(i) \tag{1}$$

where:

$p(i)$ is the percentage of the *i*-th category;

C is the number of total categories, chosen as the base to ensure the entropy value ranging between 0 and 1.

The accessibility of transport infrastructure plays a significant role in mode choice. The ease of access to public transportation makes the commuters less prone to private vehicle usage. We calculated the road network distances to the nearest MRT and bus stations as the indicators of accessibility. The density of bus stops within each TAZ is also computed.

The statistics of BE variables introduced above are summarized in Table 3.

TABLE 3 Summary of BE variables

	Mean	SD	Max	Min
FAR of public residence at origin	0.913	0.674	3.285	0.000
FAR of public residence at destination	0.693	0.626	2.933	0.000
FAR of private residence at origin	0.201	0.339	1.808	0.000
FAR of private residence at destination	0.173	0.284	1.773	0.000
FAR of commercial buildings origin	0.047	0.147	2.310	0.000
FAR of commercial buildings destination	0.297	0.559	3.744	0.000
FAR of industrial buildings at origin	0.025	0.134	1.712	0.000
FAR of industrial buildings at destination	0.011	0.074	1.495	0.000
Entropy at origin	0.516	0.124	0.949	0.000
Entropy at destination	0.552	0.104	0.949	0.000
Number of POIs at origin per km^2 (scaled by 0.001)	0.064	0.040	0.206	0.000
Number of POIs at destination per km^2 (scaled by 0.001)	0.073	0.034	0.185	0.000
Distance to bus stop (km)	0.286	0.243	4.141	0.000
Distance to MRT station (km)	1.244	0.775	8.965	0.000
Number of bus stops at origin per km^2 (scaled by 0.01)	0.114	0.061	0.344	0.000
Number of bus stops at destination per km^2 (scaled by 0.01)	0.116	0.054	0.262	0.000

Note: SD: standard deviation.

MODELS AND RESULTS

In the study, we assume that choice behavior is determined by the rational evaluation from all available choice alternatives to maximize the utility, which is influenced by trip specific attributes, BE variables, and sociodemographic characteristics of each individual. The mixed logit model with panel data structure is implemented to investigate the choice behaviors, which also allows us to capture the heterogeneity of taste across the cohorts. Each parameter follows normal distribution. For each individual, the preference, i.e. the alternative specific constant (ASC), follows the same distribution. The deterministic part of utility function V_{njt} for individual n choosing alternative j in choice situation t is:

$$V_{njt} = \alpha_{nj} + \beta'_{nj} T_{njt} + \gamma'_{nj} B_n + \delta_{nj}{}' X_n \, , \tag{2}$$

where:

T_{njt} is the vector of trip specific attributes of mode j for individual n in situation t;

B_n is the vector of BE variables of individual n;

X_n is the vector of sociodemographic variables of individual n;

α_{nj} is the ASC to estimate the inherent preference of individual n on mode j;

β'_{nj}, γ'_{nj}, and $\delta_{nj}{}'$ are the corresponding coefficients to be estimated.

The coefficient estimation algorithms for mixed logit model with panel data are elaborated in Train (*31*). The detailed explanations of the methods are not duplicated in this paper.

Two models are built for comparative purpose. The Base Model only includes trip specific and sociodemographic variables, while the BE information is incorporated in the BE Model. Both models are estimated in PythonBiogeme with 5,000 random draws (*32*). The final models are listed in Table 4 with some variables dropped due to statistic insignificance. For all standard deviation variables, the insignificant coefficients are still kept since it shows that the impact of corresponding variable is homogeneous across the samples.

TABLE 4. Mixed logit model with panel data structure

Variable	Parameter	Value (t-test)	Value (t-test)
		Base Model	BE Model
Alternative Specific Constant			
Walk	Mean	fixed at 0	fixed at 0
	SD	fixed at 0	fixed at 0
Bus	Mean	-0.569 (-2.11)†	-1.21 (-3.74)‡
	SD	0.818 (1.89)□	1.05 (4.36)‡
Ride hailing	Mean	-1.07 (-4.09)‡	-1.39 (-2.83)‡
	SD	0.057 (0.81)*	0.201 (0.9)*
On-demand AV	Mean	-0.568 (-2.56)†	-2.14 (-4.19)‡
	SD	0.758 (3.72)‡	0.00777 (0.02)*
Generalized travel cost			
Walk: Walking time (min)	Mean	-0.363 (-28.20)‡	-0.361 (-27.5)‡
	SD	0.171 (22.26)‡	0.173 (21.29)‡
Bus: Travel cost (S$)	Mean	-1.14 (-8.86)‡	-1.16 (-9.11)‡
	SD	0.436 (0.16)*	0.492 (2.12)†
Bus: In-vehicle time (min)	Mean	-0.212 (-12.10)‡	-0.203 (-12.7)‡
	SD	0.174 (9.16)‡	0.141 (8.2)‡

Bus: Waiting time (min)	Mean	-0.271 (-10.27)‡	-0.267 (-10.66)‡
	SD	0.223 (5.31)‡	0.220 (6.14)‡
Bus: Walking time to bus stop (min)	Mean	-0.214 (-10.61)‡	-0.213 (-10.91)‡
	SD	0.140 (4.14)‡	0.123 (4.07)‡
Ride hailing: Travel cost (S$)	Mean	-0.946 (-18.17)‡	-0.902 (-17.44)‡
	SD	0.470 (16.39)‡	0.436 (14.81)‡
Ride hailing: In-vehicle time (min)	Mean	-0.198 (-9.68)‡	-0.192 (-9.32)‡
	SD	0.0156 (0.58)*	0.0235 (0.75)*
Ride hailing: Waiting time (min)	Mean	-0.175 (-6.66)‡	-0.177 (-6.55)‡
	SD	0.0169 (0.25)*	0.0406 (0.76)*
On-demand AV: Travel cost (S$)	Mean	-0.984 (-18.56)‡	-0.936 (-18.53)‡
	SD	0.465 (13.54)‡	0.419 (12.74)‡
On-demand AV: In-vehicle time (min)	Mean	-0.195 (-11.0)‡	-0.193 (-10.99)‡
	SD	0.0288 (1.16)*	0.00162 (0.05)*
On-demand AV: Waiting time (min)	Mean	-0.222 (-8.50)‡	-0.217 (-8.41)‡
	SD	0.0310 (0.58)*	0.0218 (0.46)*
Built environment			
Bus: Distance to bus stop (km)	Mean	-	-1.13 (-2.18)†
	SD	-	2.07 (3.37)‡
Bus: Distance to MRT station (km)	Mean	-	0.712 (5.45)‡
	SD	-	0.18 (1.28)*
Ride hailing: FAR of commercial buildings at origin	Mean	-	1.07 (2.28)†
	SD	-	0.23 (0.38)*
Ride hailing: FAR of industrial buildings at origin	Mean	-	1.69 (2.69)‡
	SD	-	0.474 (0.63)*
Ride hailing: Entropy at origin	Mean	-	1.24 (1.84)□
	SD	-	0.0549 (0.14)*
Ride hailing: Number of bus stops at origin per sq. km	Mean	-	-2.74 (-2.62)‡
	SD	-	0.551 (0.48)*
On-demand AV: distant to MRT station (km)	Mean	-	0.220 (1.87)□
	SD	-	0.112 (0.35)*
On-demand AV: FAR of commercial building at origin	Mean	-	0.939 (1.8)□
	SD	-	0.205 (0.29)*
On-demand AV: FAR of industrial buildings at origin	Mean	-	2.230 (3.27)‡
	SD	-	1.62 (1.68)□
On-demand AV: FAR of public residence at destination	Mean	-	0.409 (3.01)‡
	SD	-	0.28 (0.93)*
On-demand AV: Entropy at origin	Mean	-	2.06 (2.98)‡
	SD	-	1.28 (2.28)†
On-demand AV: Number of POIs at destination per sq. km	Mean	-	1.74 (2.33)†
	SD	-	0.11 (0.05)*
On-demand AV: Number of bus stops at origin per sq. km	Mean	-	-2.46 (-2.28)†
	SD	-	0.276 (0.13)*
Sociodemographic variables			
Ride hailing: household income less than S$4,000 per month	Mean	-0.509 (-2.81)‡	-0.461 (-2.59)‡
	SD	0.200 (0.47)*	0.402 (0.98)*

On-demand AV: household income less than S$4,000 per month	Mean	-0.497 (-2.81)‡	-0.445 (-2.61)‡
	SD	0.300 (0.62)*	0.302 (0.64)*
Statistical summary			
Number of individuals		1,242	1,242
Number of observations		8,689	8,689
Number of random draws		5,000	5,000
Initial log-likelihood at zero		-10832.448	-10832.448
Final log-likelihood		-6581.302	-6527.452
Adjusted McFadden ρ^2		0.390	0.392
Akaike Information Criterion		13218.604	13170.903
Bayesian Information Criterion		13416.558	13580.952

*Note: * Insignificant; □ p<0.1; † p<0.05; ‡ p<0.01. SD: standard deviation.*

Comparing with the two models, the coefficients of trip specific and sociodemographic variables are quite robust. Incorporating additional BE variables, the coefficients do not change significantly. It implies that the impacts of BE variables are independent from trip specific and sociodemographic variables. In the BE Model, the ASC of each travel mode shifts, however, the goodness-of-fit of the model remains at the same level. The AIC and BIC values indicate that the slight growth of McFadden ρ^2 is simply resulted by adding more variables into the BE Model. Hence, the results from the two models imply that, although BE variables do not make the model significantly fit better, it offers more details in explaining the impacts of BE on individual's preference on each travel mode.

For all parameters, the signs are reasonable. The influence of bus travel cost is more sensitive than the costs of chauffeured ride hailing and on-demand AV. The absolute value of bus in-vehicle travel time is greater than the values of the two other motorized modes. Comparing with ride hailing and on-demand AV, the impacts of trip specific variables are mostly consistent except waiting time. The survey respondents prefer to get onto the on-demand AV in fewer minutes. The standard deviation of the generalized travel cost of walk and bus are statistically different from zero, which implies that people's attitude towards these two modes are diverse. The impacts of travel cost and waiting time of ride hailing and AV are also heterogeneous across the cohorts, whereas the impact of the corresponding in-vehicle time is not.

In terms of sociodemographic variables, we find that people from lower income group do not prefer ride hailing and on-demand AV comparing with bus and walk. The decline in utility of ride hailing is slightly greater than the decrease of on-demand AV utility. As for the taste variation, we can find the impacts are harmonious among the samples.

Look into the impact of BE variables. The estimated parameters of distance to bus stop suggest that people are more likely to choose bus if there a nearby bus stop. The positive sign of distance to MRT stations demonstrates that longer distance leads to increased market share of bus and on-demand AV, while bus would obtain a higher increment of market share comparing with on-demand AV. Ride hailing is also affected by BE. The FARs of commercial and industrial buildings at origin present positive effects on choosing ride hailing. Similar impacts can also be observed in AV mode choice. The FARs of commercial and industrial buildings at origin are found positive to the utility of on-demand AV as well. And, the FAR of public residence at destination also shows similar positive impact. The entropy of origin is found positive to the utility of ride hailing and on-demand AV choice. A plausible explanation is that people who lives in an area with higher mixture of socioeconomic activities are more likely to choose on-demand services for the first mile. As for the infrastructure variables, in the areas with high density of bus stops, people are less likely to use ride hailing and on-demand AV. The density of POIs at destination is found positive to the utility of on-demand AV as well. In terms of the taste variation of BE, only a few of them show significant variation of taste. The impact of entropy and industrial density at origin varies across the samples for AV mode choice. The samples also present various attitudes towards the distance to bus stop in terms of bus choice. The impacts of other BE variables are all found homogeneous among the samples.

POLICY IMPLICATION WITH SIMULATION PRACTICE

Singapore has planned to deploy on-demand AVs in several areas including Punggol, Tengah, the Jurong Innovation District (JID), Toa Payoh and the Central Area. To evaluate whether these areas are the ideal places for AV deployment from the perspective of first-mile travel demand, we thus implement the choice model developed in this study to simulate the potential modal share of AV in different planning areas (PA).

The samples for simulation are set as the individuals who use the MRT for work, extracted from the HITS data in 2012. The samples from HITS are randomly sampled from all households in Singapore with approximately 1% of the total households. In this way, the simulation of travel demand is close to the real-world situation, which can better reflect the potential market share after the deployment of on-demand AV. The household income for each individual in 2012 is converted to the rates in 2017 based on the core inflation index (*33*).

Similar to the survey framework, the dynamic variables like travel time and travel cost of walk, bus and ride hailing for each individual are calculated using Google Maps based on their first-mile origins and destinations. The static variable such as waiting time of bus and ride hailing is set equal to the corresponding average value derived from HITS data. All generalized travel cost variables of AV are set equal to those of ride hailing for comparative purpose. After data cleaning, 11,545 individuals are finally obtained for simulation. The spatial representativeness of HITS samples is validated by Mo et al. (*25)*. Two simulation scenarios are designed according to the two behavioral models, respectively. The individuals choose the first-mile travel modes during the simulation. For each scenario, we replicate the simulation for 10,000 runs. Based on the choice probabilities of each travel mode of the individuals, the market share of each mode is aggregated at the level of PA. To relieve random errors, the PAs with less than 10 samples are discarded from the results. Thus, although Tengah is planned for future AV deployment, the area is excluded from the analysis due to insufficient data.

The simulation results are visualized in the following figures. The PAs with red boundaries are the areas considered for on-demand AV pilot deployment. The two behavioral models with similar goodness-of-fit values do not necessarily lead to the same market share outputs, especially with a larger sample from HITS data for simulation. Thus, although the overall market shares of the two models are consistent with each other, there is a slight increase (about 1.9%) of the total market share of AV with the inclusion of BE impacts.

Figure 4 presents the first-mile modal shares resulted by the Base Model. In most of the PAs, by keeping the fares of all travel modes the same as the current pricing scheme, walk and bus are still the dominant selections for first mile connections, even after the deployment of AV. Looking at the AV pilot deployment areas, the market shares of AV in Toa Payoh, Punggol, Jurong West, and the Central Area are all very low, in which the majority of residents would still prefer to walk to the MRT stations. The residents in Nanyang are more likely to choose motorized travel modes since the area is distant from the MRT stations. Approximately one quarter of the residents in the area would choose AV as their first mile travel mode.

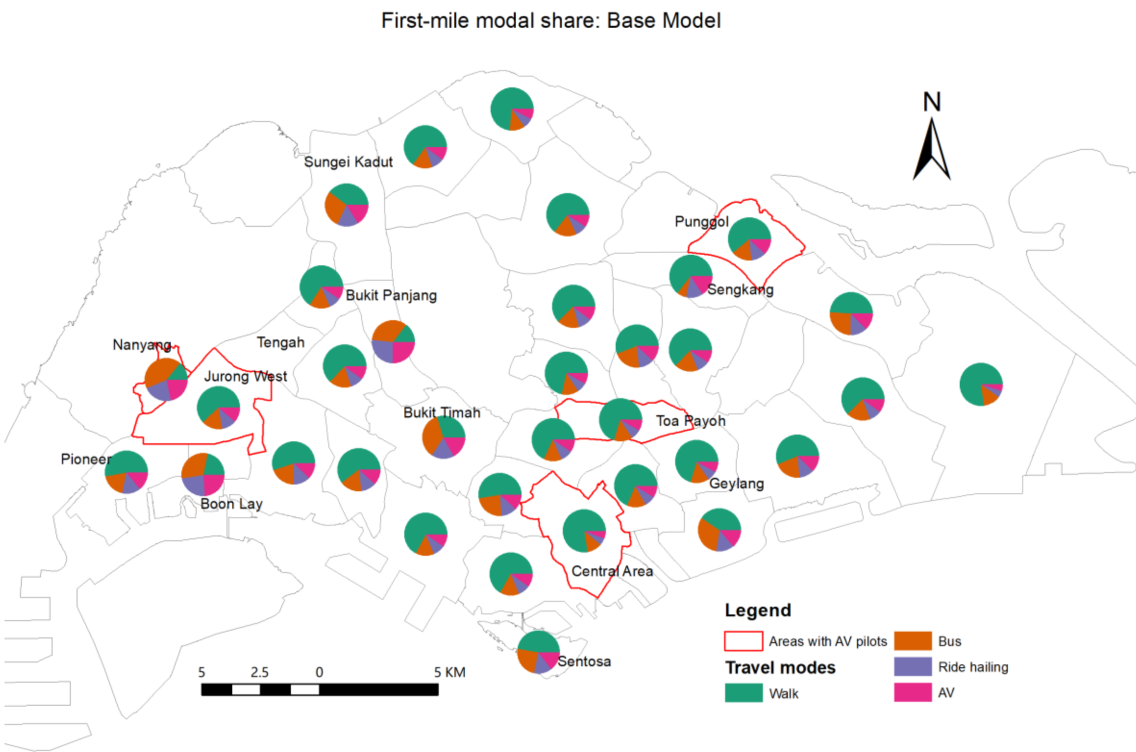

FIGURE 4. First-mile modal share in base model

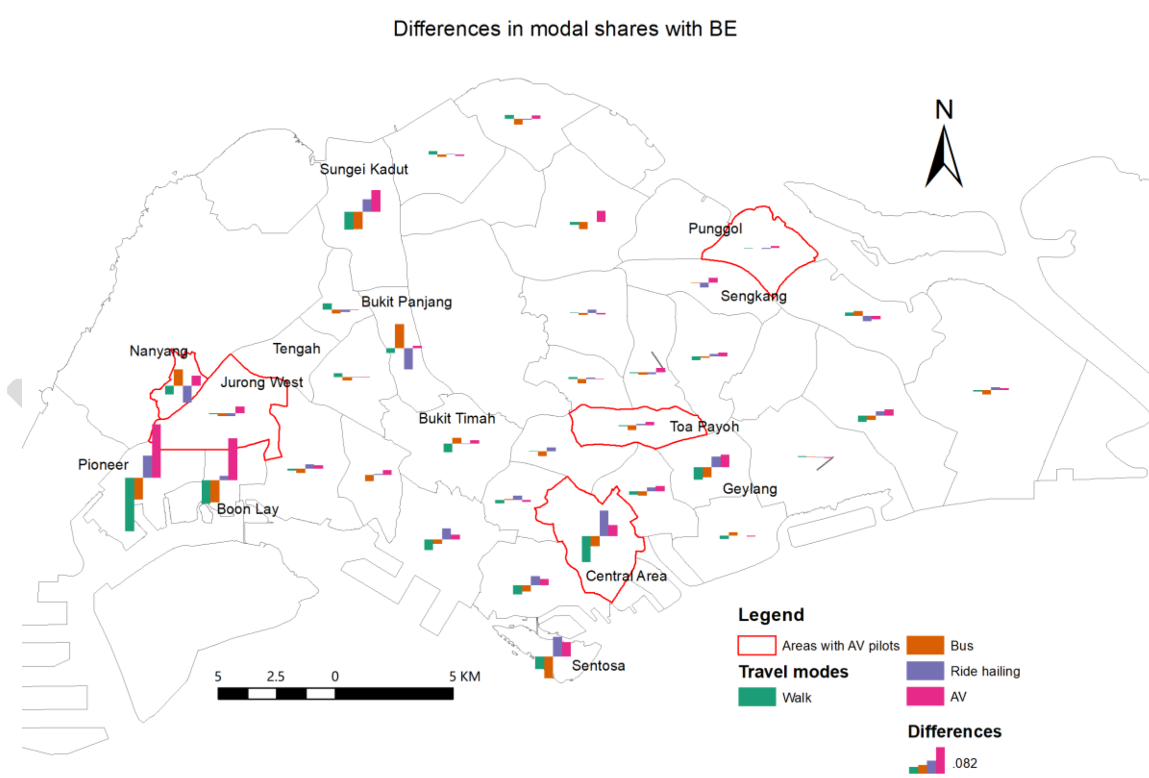

FIGURE 5. Differences in modal share with BE

Figure 5 illustrates the changes in mode shares taking into account the impacts of BE. With the inclusion of BE variables, the change of market share of each travel mode largely varies by PA. In Punggol and Toa Payoh, the market share of AV only slightly increases. In the Central Area, more people would choose ride hailing and on-demand AV instead of walk and bus. Some residents from Jurong West who choose bus or ride hailing according to the Base Model may use AV for first mile travel. The shares of bus and AV in Nanyang increase while the shares of walk and ride hailing decline. In other areas, the two PAs—Pioneer and Boon Lay—at the south of Jurong West enjoy the greatest increase of AV share thanks to the BE Model. In Sunget Kadut (located in the north), the Sentosa Island, and Geylang (adjacent to Toa Payoh), we are able to find significant increase of the modal share of on-demand AV.

Figure 6 and Figure 7 present the spatial distribution of AV mode shares simulated by the Base Model and the BE Model, respectively. Comparing with the two figures, in Figure 6, the spatial distribution of AV mode share resulted by the Base Model is quite dispersed with Moran's *I* equal to 0.23. With the inclusion of BE impacts, in Figure 7, the distribution of AV mode share becomes more spatially clustered with Moran' *I* value increasing to 0.35. Incorporating the impact of BE, the spatial distribution of the highest AV demand areas shifts to the peripheral areas of the country. Specifically, Sentosa and Pioneer become the top-ranking areas with the highest demand of AV. Visually, the demand of AV for the first mile in the western part is in general greater than that in the east. Focusing on the PAs with AV pilot deployment plans, however, except Nanyang, in other areas, no matter which behavior model is adopted, the AV demand does not rank at the top 20% quantile.

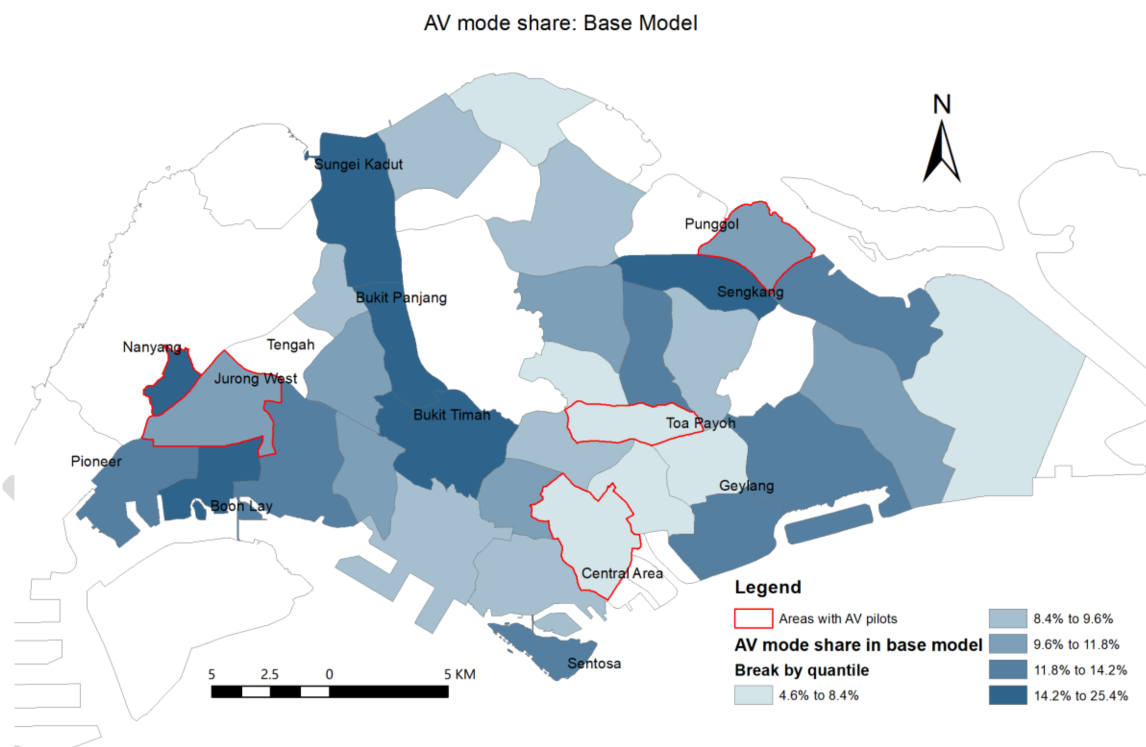

FIGURE 6. Spatial distribution of AV mode shares resulted by Base Model

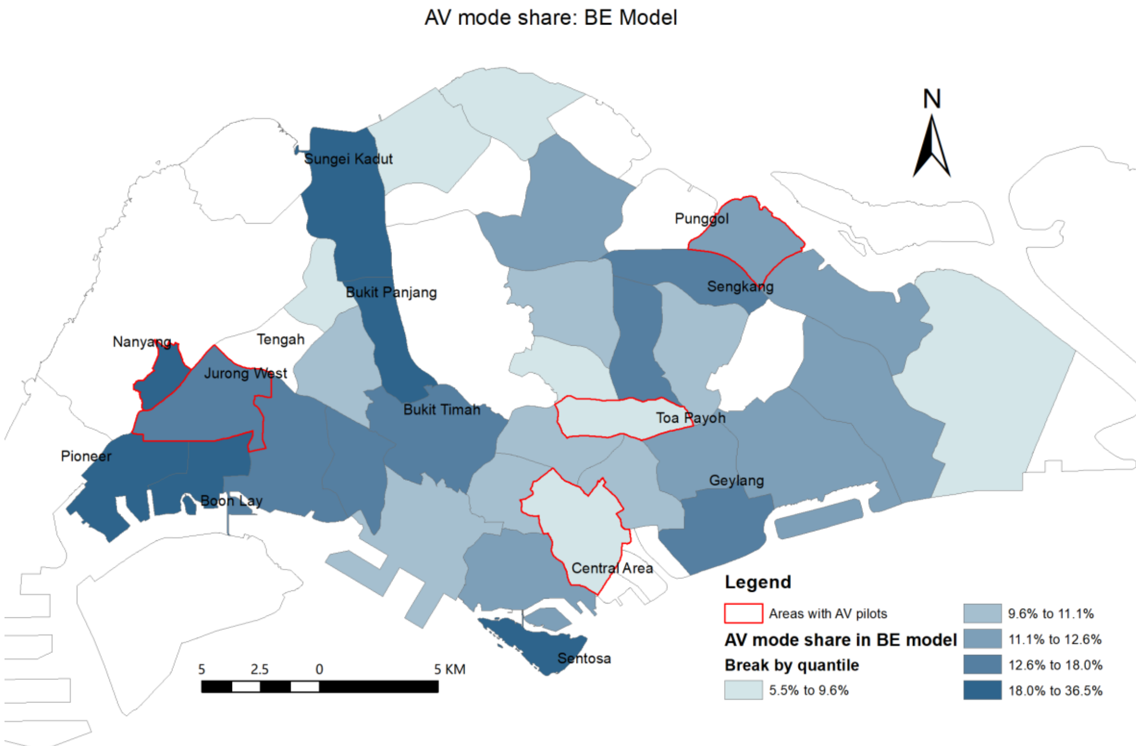

FIGURE 7. Spatial distribution of AV mode shares resulted by BE Model

Comparing the simulation results with the analysis of public transit card data conducted by Shen et al. (*8*), higher first-mile bus demand does not necessarily lead to the highest potential first-mile AV demand. By keeping the current fare structures the same, there are no consistent evidences showing that people who currently choose bus for first mile connection would shift to on-demand AV after the deployment.

Revisiting current planning for AV pilot deployment in Singapore, the potential demand of AV along current JID corridor—from Nanyang, Jurong West, to Tengah—is likely to be lower than the southern areas next to the corridor including Pioneer and Boon Lay. From the first-mile demand point of view, to boost the potential market share of AV, comparing with the current plans, the southern corridor from Nanyang to Pioneer and Boon Lay could be a better choice. Similarly, instead of Punggol, its the neighboring PA, Sengkang, may also be a better candidate area to deploy the on-demand AV service. In addition, neither Toa Payoh nor the Central Area is an ideal place for first-mile AV. Instead, decision makers may consider to deploy the on-demand AV service in Sentosa Island or along the Rail Corridor (*34*) from Sungei Kadut to Bukit Timah to enhance the first mile connectivity in these areas.

CONCLUSION AND DISCUSSIONS

This study investigates travel mode choice with on-demand AV as an available alternative. We specifically focus on the impacts of BE on the first-mile scenarios in Singapore. A dynamic survey is developed to automatically generate realistic first-mile trip scenarios according to the respondents' dwelling locations. BE variables are calculated around dwelling locations and are integrated into the models to explore the influence on mode choice with AV. Two mixed logit models with panel data structures are adopted to the model the first-mile choice behaviors. Comparing with the Base Model, the inclusion of BE variables does not significantly affect the coefficients of trip specific and sociodemographic variables. The modeling results indicate that BE does not greatly improve the overall goodness-of-fit of the models, but it offers more details to help us interpret the individual preferences in mode choice.

We further forecast the first-mile mode choice of 11,545 individuals from the HITS data. The results shed light on evaluating current plans for AV pilot deployment in Singapore to see whether there is enough demand of last-mile trips using AV. It shows, except for Nanyang, all other areas do not rank at the top one-fifth quantile with the highest AV mode shares. Based on the forecasting, the study recommends some pilot areas for future AV deployment where the mode share of AV is potentially high.

This study attempts from a new angle to evaluate current planning for AV deployment by exploring the first-mile mode choice behaviors and demands. Nonetheless, we acknowledge that the actual decision making process for AV deployment is a much more sophisticated practice. Other constraints, e.g. land availability, supportive infrastructures, etc., could also play a critical role. In addition, travel demand changes dynamically with fare schemes and service quality. For future work, a dynamic demand-supply interactive simulation incorporating behavioral models and the optimization of AV operation should be considered, in order to provide a full picture to understand the future scenarios with AV.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Y. Shen, J. Zhao; data collection: Y. Shen, B. Mo, J. Zhao; analysis and interpretation of results: Y. Shen, B. Mo, X. Zhang; draft manuscript preparation: Y. Shen, B. Mo, X. Zhang. All authors reviewed the results and approved the final version of the manuscript.

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