Private Autonomous Vehicles and Their Impacts on Near-Activity Location Travel Patterns: Integrated Mode Choice and Parking Assignment Model

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ABSTRACT

The goal of this study is to analyze the impact of private autonomous vehicles (PAVs), specifically their near-activity location travel patterns, on vehicle miles traveled (VMT). The study proposes an integrated mode choice and simulation-based parking assignment model and an iterative solution approach to analyze the impacts of PAVs on VMT, mode choice, parking lot usage, and other system performance measures. The dynamic simulation-based parking assignment model determines the parking location choice of each traveler as a function of the spatial-temporal demand for parking from the mode choice model, while the multinomial logit mode choice model determines mode splits based on the costs and service quality of each travel mode determined partially by the parking assignment model. The paper presents a case study to illustrate the power of the modeling framework. The case study varies the percentage of persons with a private vehicle (PV) who own a PAV vs. own a private conventional vehicle (PCV). The results show that PAV owners travel an extra 0.11 to 1.51 miles compared with PCV owners on average. Hence, as the PCVs are converted into PAVs, total VMT in the network increases substantially. The results further indicate that VMT can be reduced by adjusting parking fees and redistributing parking lot capacities. The significant increase in VMT from PAVs implies that planners should develop policies to reduce PAV deadheading miles near activity locations, as the automated era comes closer.

Keywords: Autonomous Vehicles, Parking, Mode Choice, Vehicle Miles Traveled, Integrated Modeling, Fixed-point Problem, Simulation, Deadheading

1 INTRODUCTION

Over the last ten years, a large volume of research focused on modeling and predicting the impacts of autonomous vehicles (AVs) on travel behavior, travel demand, and transportation systems broadly. Although AVs are expected to result in more efficient vehicle operations that improve traffic flow, most studies suggest that AVs will also increase overall vehicle miles traveled (VMT) (*1*). Given that AVs are not yet widely available, their overall impact on travel demand and traffic congestion is still uncertain (*2*). However, in order to plan for AVs, including allocating resources for infrastructure investments and setting policies and regulations, it is important to model, understand, and forecast the potential impacts of AVs on transportation systems under a variety of different conditions.

One particular concern about AVs is that they are expected to drastically increase overall VMT and thereby increase congestion, energy consumption, and vehicle emissions. The existing literature identifies a variety of behavioral changes stemming from the introduction of AVs that may increase private vehicle (PV) usage and overall VMT. For example, AVs are expected to decrease the burden or disutility of PV travel as AVs do not require a traveler to drive the vehicle, an onerous and unproductive task, thereby making PV travel less costly and increasing overall travel and travel distances for a variety of trip purposes (*3–5*). As another example, people without driver's licenses, seniors, and people with medical conditions are expected to make more trips and increase their vehicle-based travel when AVs enter the market (*6*). From a long-term land use perspective, some people may change their home locations and work locations as a result of AVs reducing travel costs to/from major activity locations (*7–9*). Also, the improved convenience of PVs will attract current transit users to switch trips to PAVs, thereby increasing VMT (*10*, *11*).

Additionally, as drivers become riders in PAVs, travel patterns of PAVs are likely to diverge from travel patterns in private conventional (i.e., non-autonomous) vehicles (PCVs). Rather PAV travel patterns are likely to involve dropping off travelers at their exact activity locations and traveling empty (i.e., deadheading) to another location to park during the activity. While deadheading in PAVs is similar to current taxi and ride-hailing services, in the case of taxis and ride-hailing, the next location is likely a traveler pickup spot, whereas in the case of PAVs, the next location is likely a parking spot. Both PAVs and conventional ride-hailing will inevitably generate deadheading miles, i.e., vehicles driving without passengers. However, the degree of deadheading in both cases depends on a variety of factors. Recent studies show that deadheading miles from ride-hailing services, unsurprisingly, increase road network congestion (*12*, *13*).

This study focuses on the near-activity location travel associated with PAVs and their impact on VMT relative to the current world with only PCVs. Figure 1 displays potential travel patterns for PCVs and PAVs for the same person trip from a home location to an activity location. Figure 1 shows that PCV travel typically involves a traveler driving to a parking lot and then walking to the activity location from the parking lot. However, in the case of PAVs, the AV drives the traveler directly to work, negating walking, and then deadheads to a parking location. Notably, because the traveler does not need to walk from parking location to activity location, the traveler is more willing to choose parking locations farther away from the activity location (or allow the AV itself to choose further away parking locations) if they are cheaper.

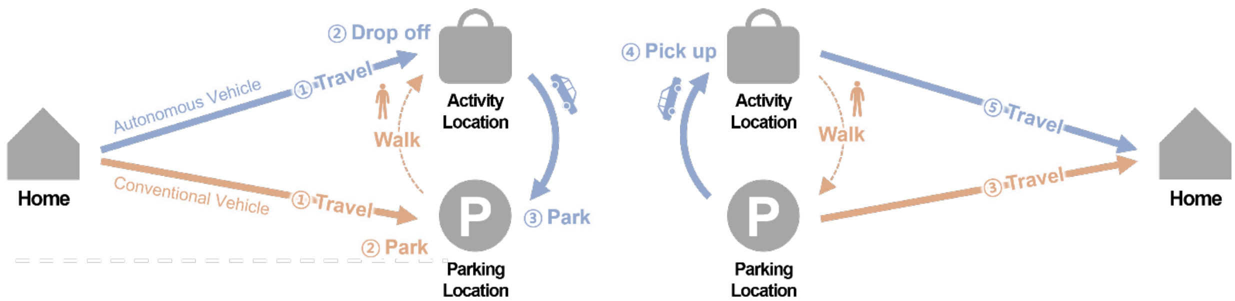

Figure 1 Travel Pattern of PCVs and PAVs

The goal of this paper is to develop a modeling framework in order to analyze the potential impacts of PAVs on near-activity travel patterns and overall VMT. Near-activity travel patterns for PVs denote the travel between activity locations and parking lots by vehicles and people, in the case where the parking lot is not at the same location as the activity. To model this problem, this paper presents an integrated parking location choice and mode choice model. The parking location choice model considers factors such as parking fee, parking lot capacity and congestion, driving cost per mile, walking distance for PCV travelers, and waiting time for PAVs to pick up travelers for their return home trip. The mode choice model captures the potential shifts between transit, shared vehicles like ridesourcing and taxi, and PVs as a function of the cost and service quality provided by each of these modes. Moreover, by integrating the mode choice and parking choice model, the framework captures the balancing effects of mode shifts toward PAVs (and to a lesser extent PCVs) and parking lot capacity and congestion impacts on the attractiveness of PAVs and PCVs.

The study also presents an iterative solution approach to solve the integrated mode choice and parking location choice problem. The output of the model and solution algorithm includes mode shares, VMT, parking lot occupancy, traveler wait times, traveler walk distances, and traveler in-vehicle travel time (IVTT). By varying the percentage of PAVs and PCVs in various scenarios, the study aims to analyze the impact of PAVs on overall VMT. The authors believe integrating mode choice with parking location choice is critical for assessing the impacts of PAVs on near-activity VMT, for the reason that PV travel is likely to increase in a future with AVs compared to the current transportation system without AVs.

This paper makes several contributions to the existing literature. First, it introduces an integrated mode choice and parking assignment problem with PAVs, and formulates it as a fixed-point problem, in order to analyze the impacts of PAVs on near-activity travel patterns and VMT in particular. Previous research aims to analyze the impacts of PAVs on travel patterns and VMT, but those studies do not explicitly integrate mode choice and parking assignment. Second, this paper proposes a novel simulation-based parking assignment model to evaluate near-activity travel patterns, VMT, parking lot congestion, traveler walking distance, and other important travel attributes. Third, the paper presents an efficient iterative solution approach to solve the integrated mode choice and parking assignment problem. Fourth, the paper presents valuable insights into the trade-offs between VMT, travel time, and travel costs when comparing a system with PCVs vs. a system with PAVs.

The remainder of this paper is structured as follows. The next section provides a brief review of the existing literature. The following section presents the mathematical formulation of the integrated mode choice and parking location choice problem. The following section presents an iterative solution approach to solve the integrated model. A case study based on an artificial central business district is outlined in the following section. The next section presents computational results from the case study and associated scenario analyses. The penultimate section discusses the implications of the model results. The final section concludes the paper.

2 LITERATURE REVIEW

Although many studies analyze factors related to AVs that impact travel behavior, relatively few studies analyze the impact of AVs on near-activity location travel and parking. Moreover, most parking studies related to AVs focus on microscopic topics such as optimizing parking lot configurations and how to find a parking location more efficiently (*14–17*). Conversely, the current study focuses on parking and AVs across a transportation network to understand and forecast the potential impacts of AVs on VMT, parking lot usage, and other relevant metrics for transportation planning purposes. This section provides a brief review of studies that analyze the relationship between parking, travel behavior, and transportation system performance for PCVs before reviewing the small set of recent studies that incorporate PAVs alongside the other factors.

The parking location choice problem for PCVs is well established in the literature. Feeney provides a review of studies in the 1970s and early 1980s covering the impact of parking policy measures on travel demand (*17*). The behavioral models (mostly logit models) show that factors such as parking fees and time costs (e.g. walking time) impact mode choice and travel behavior (*18*). Unlike most of the literature that relies on revealed preference data, Axhausen and Polak employ stated preference data to estimate a parking choice model (*19*). Specifically, they create a parking type choice set that includes off-street, surface lot, and multi-story parking. Two other studies develop and use agent-based parking choice models within MATSim (*20*, *21*). Bischoff and Nagel find that incorporating parking choice in MATSim for Klausenerplatz in Berlin increase total VMT estimates by almost 20% (*21*). Habib et al. incorporate parking type choice alongside activity scheduling decisions within an activity-based travel demand model (*22*).

More recently, several studies analyze changes in parking behavior related to PAVs. Table 1 provides a summary of these studies alongside a summary of the current study. Levin and Boyles adopt the conventional multi-class four-step trip-based model to predict PAV travel patterns assuming that some PAVs will drive a traveler to their activity location before deadheading to the same traveler's origin (home) to avoid parking fees near the high-demand activity center (*23*). In a PAV-only scenario, Childress et al. find a 50% discount in parking fees results in a significant increase in VMT (*24*). Zhang et al. suggest that PAVs will generate unoccupied VMT due to the reduction of household vehicle ownership and deadheading (*25*). Zhang et al. develop an integrated parking choice and route choice model (*26*). Harper et al. predict that some PAVs will greedily search for more distant and economical parking spots including unrestricted parking areas rather than downtown parking lots, thereby increasing VMT (*27*). On the other hand, Zhao et al. propose a centrally controlled parking system that collects travelers' destination information and dispatches the vehicles to the parking lots and finds that this can reduce VMT (*28*).

It is not possible to compare the results of those studies directly since they each make different assumptions and employ different modeling approaches. However, there are several emerging key factors that illustrate the relationship between AVs, travel behavior, and VMT. For example, parking fees and walking time are the most important factors in parking location choice (*17–19*, *24*, *27*). Not easily perceived, but a vehicle's cost per mile is a factor as well. For PAVs, waiting time should be included in behavioral models since travelers need to wait for pickup after calling the AV, unless the traveler summons the PAV to arrive at the pickup point first, in which case the PAV may have to wait for the traveler. The model in this study incorporates all these factors into a utility maximization framework for mode choice and parking location choice.

Table 1 Comparison of PAV Studies on Parking Behavior

Study	Purpose	Approach	Parking-related Findings
Levin & Boyles (2015) (*23*)	Analyze impact of AVs on travel behavior and network performance	Four-step trip-based travel forecasting model	PAVs increase VMT due to deadheading to cheap parking
Childress et al. (2015) (*24*)	Quantify impacts of AVs on travel behavior and network performance	Activity-based travel forecasting model	Improved road capacity, reduced VOT, and discounted parking fees increase PAV demand and VMT.
Zhang et al. (2018) (*25*)	Quantify excess VMT stemming from vehicle deadheading	Household travel model. Greedy scheduling algorithm for required household vehicles. Mixed-integer program for unoccupied VMT.	Reduction of household vehicles increases VMT due to unoccupied PAV travel.
Zhang et al. (2019) (*26*)	Quantify network equilibrium patterns under AV parking behavior	Integrated route choice and parking assignment choice model and solution approach	PAVs increase traffic congestion due to parking search. Some PAVs will park at home.
Harper et al. (2018) (*27*)	Evaluate impact of AVs on VMT, emissions, and parking revenues	Agent-based parking simulation model on grid network with greedy parking lot selection	PAVs park at distant and economical parking locations and increase VMT.
Zhao et al. (2021) (*28*)	Analyze improvements in congestion under centralized parking dispatch	Optimization of parking control with macroscopic fundamental diagram	Optimized parking assignment reduces cruising VMT for parking
This study	Estimate impacts of PAV parking travel patterns on VMT and PV demand	Integrated mode and parking location choice model. Iterative solution approach.	PAVs increase demand for PV travel and as a result, VMT increases.

3 PROBLEM FORMULATION

This study presents the integrated mode choice and parking assignment problem, wherein the parking assignment model captures congestion and capacity constraints in parking lots throughout the analysis region. Since the demand for parking is a function of mode choice (i.e., higher PV demand increases parking lot congestion), and mode choice is a function of parking congestion (i.e., congestion in parking lots reduces demand for PVs), this study models the integrated mode choice and parking assignment problem using a fixed-point problem formulation. In general, a fixed point of a function $f(\cdot)$ is a value p such that $f(p) = p$, or put another way, the value p is unchanged by function $f(\cdot)$ (*29*). The variable p can be a scalar or a vector.

Eqn. 1 displays the general form of the integrated mode choice and parking assignment model in the form of a fixed point problem. A solution to Eqn. 1 is a multi-dimensional array of probabilities, $\boldsymbol{p}$, that when input into $f_m\left(f_p(\cdot)\right)$ remain unchanged. The parking function $f_p(\cdot)$ in this study does not have a straightforward functional form, rather this study employs a dynamic simulation-based parking assignment model that is detailed in the next section. Eqn. 2 shows that the function $f_p(\cdot)$ is non-separable because the mode splits ($\boldsymbol{p_{odt}}$) between each origin $o \in O$ and destination $d \in D$ at time interval $t \in T$ impact the service quality, price, and therefore parking location choice for travelers using the parking system between all origins, all destinations, and all future time periods. Conversely, the mode choice function, $f_m(\cdot)$, displayed in Eqn. 3, which returns mode splits for travelers going from origin $o \in O$ to destination $d \in D$ at time interval $t \in T$, is separable by origin, destination, and time interval.

$$\boldsymbol{p} = f_m\left(f_p(\boldsymbol{p})\right) \tag{1}$$

$$\boldsymbol{q} = f_p(\boldsymbol{p}) \tag{2}$$

$$\boldsymbol{p_{odt}} = f_m(\boldsymbol{q_{odt}}) \tag{3}$$

Where,

M:	set of modes in the transportation system, indexed by $m \in M$
O:	set of origin zones in the transportation network, indexed by $o \in O$
D	set of destination zones in the transportation network, indexed by $d \in D$
T	set of time intervals in the analysis period, indexed by $t \in T$
K_m:	set of service quality and cost/price attributes associated with mode m, indexed by $k \in K_m$
p_{odtm}:	choice probability for mode m, for a traveler going from origin o, to destination d, and departing at time interval t.
$\boldsymbol{p_{odt}}$:	vector of mode choice probabilities for origin o, destination d, and departing time interval t, with dimension $\lvert M \rvert$.
$\boldsymbol{p}$:	multidimensional array of mode choice probabilities for all modes, origins, destinations, and time intervals, with dimension $\lvert M\rvert \times \lvert O\rvert \times \lvert D\rvert \times \lvert T\rvert$
$\boldsymbol{q}$:	multidimensional array of service quality and price attributes for all modes, origins, destinations, and time intervals, with dimension $\lvert M\rvert \times \lvert O\rvert \times \lvert D\rvert \times \lvert T\rvert \times \lvert K\rvert$

The next section describes the detailed agent-based parking simulation model, $f_p(\cdot)$. The next section also provides the functional form and the parameters for the mode choice function, $f_m(\cdot)$, which is a straightforward multinomial logit model.

4 SOLUTION APPROACH

Figure 2 displays the proposed iterative solution approach to solve the integrated mode choice and parking assignment problem. The remainder of the section describes the iterative solution approach along with the model input and output.

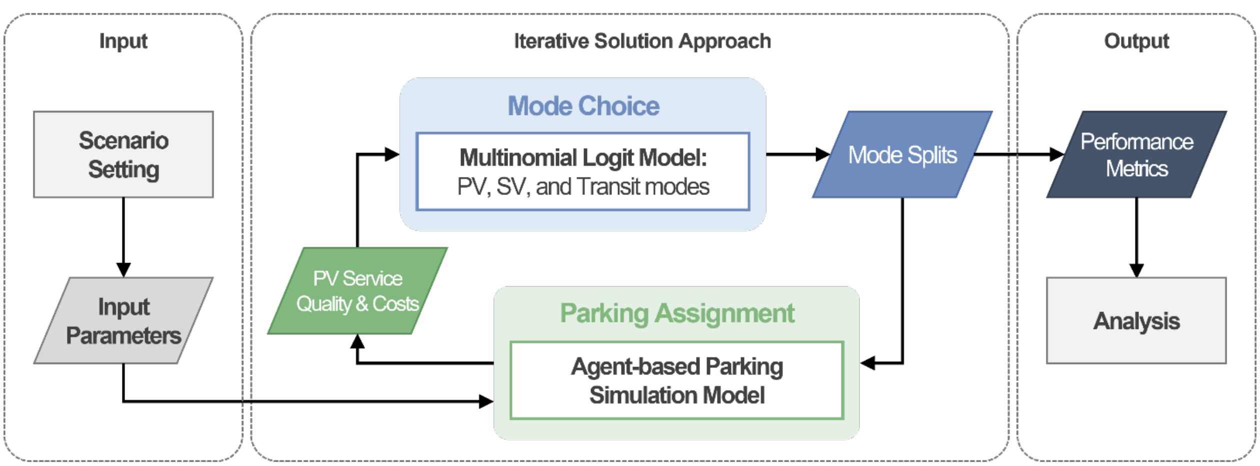

Figure 2 Solution Approach

4.1 Model Inputs

The left-most box labeled 'Input' in Figure 2 includes a scenario setting box that leads into an input parameters box. This study performs sensitivity and scenario analyses based on changes in a variety of model parameters. These parameters and the changes to them are detailed in later sections. The input data and parameters in this study include the available travel modes, mode choice model parameters, fixed modal attributes for non-PV modes, the location, capacity and price of parking lots, parameters for the parking congestion model, the transportation network, and demand data including trip origins and destinations. The following subsections provide details about the available travel models and the mode choice model parameters.

4.1.1 Travel Modes

This study incorporates three types of high-level travel modes, PVs, shared vehicles (SVs), and public transit. PV includes PCV and PAV. SV includes shared-use automated vehicles (SAVs,) ride-hailing and ride-sharing services, and taxis. SV travelers wait for a vehicle, travel inside an SV, pay a fare, and receive door-to-door service. Public transit effectively refers to high-capacity buses. Transit riders walk to a bus stop, wait for a bus, pay a fare, travel inside the bus as a rider, and walk to their destination—they may also need to transfer between routes, but this study assumes transfers are not necessary.

Specific scenario details are given in the Case Study section; however, it is important to note that each traveler has access to a single PV—either a PCV or PAV but not both—in this study. Additionally of note, in the scenarios with all PCVs, SVs are conventional vehicles (SCVs); conversely in the scenarios with all PAVs, the SVs are all SAVs.

4.1.2 Mode Choice Model Parameters

Important mode choice model parameters include the disutility of travel time for in-vehicle travel and out-of-vehicle travel (walking and waiting) and the disutility of travel costs. Combining the disutility of travel time and travel costs produces estimates of a user's value of time (VOT). According to review papers and reports, VOT varies widely depending on a variety of factors (*19*, *30*). Axhausen and Polak find a wide range of walking VOT estimates ranging from \$1.35/h to \$47.43/h in the mode choice context and \$7.67/h to \$58.21/h in the parking choice context (*19*). Caltrans uses the following VOTs: \$13.65/h for automobile and transit in-vehicle VOT and \$27.30/h for transit out-of-vehicle VOT in 2016 dollars (*31*). Kolarova et al. estimate the VOT from the German National household travel survey data segmented by mode and income class (*3*). Based on the middle-income class's PCV commuting trips (\$8.18/h), the other values of in-vehicle VOT are \$5.26/h, \$8.72/h, and \$4.89/h for PAV, SAV, and public transit, respectively. The walking VOT is \$12.03/h, while the AV and public transit waiting VOT are \$9.49/h and \$7.45/h, respectively. Zhong et al. provide ranges for the VOT for PCV, PAV, and SAV in the United States by place of living: \$9.36/h (rural) to \$53.71/h (urban) for PCV; \$7.71/h to \$40.89/h for PAV; and \$8.64/h to \$46.53/h for SAV (*5*). This study mostly uses the values in Kolarova et al. (*3*).

Moreover, this study uses \$0.50/mi as the cost per vehicle mile of travel, based on the 2020 electric vehicle cost provide by the American Automobile Association (*32*).

According to several studies about 40% of a ride-hailing service travel is deadheading miles (*13*, *33*). In other words, when one mile of PCV travel from an origin to a destination (except the parking travel distance) is changed to a ride-hailing vehicle travel, the travel distance becomes 1.67 miles (67% extra travel). Considering that PAVs do not cruise to find and then pick up another passenger, the PAV's VMT increase depends on the parking location finding travel distance.

4.2 Iterative Solution Approach

The middle portion of Figure 2 displays an overview of the proposed solution approach that involves iterating between the mode choice model and the dynamic simulation-based parking assignment model. In the iterative process, the outputs of the parking assignment model are the performance of the transportation system, specifically the costs and service quality attributes associated with PAV and/or PCV travel. Given that the parking model is agent-based, these cost and service quality attributes are available at the agent level and can easily be aggregated over time and space. The costs and service quality attributes for the other modes—transit and SV—are fixed in this study. The costs and service quality modal attributes for PVs from the parking assignment model are the inputs to the mode choice model, alongside the fixed modal attributes for SVs and transit. The outputs of the mode choice model are the modal splits, which are the inputs for the next iteration of the parking assignment model. This iterative process repeats until there is consistency between the mode choice model and the parking assignment model in terms of modal service quality/costs and modal splits.

The following two subsections describe the dynamic simulation-based parking assignment models and the multinomial logit mode choice model, respectively.

4.2.1 Dynamic Simulation-based Parking Assignment Model

The mode choice model returns modal splits, $\boldsymbol{s^n}$, where the n superscript denotes the current iteration number. Given that the modal attributes for SV and transit are fixed, and these modes do not use the parking lots, only the modal splits for PV are needed as input for the parking assignment model, $\boldsymbol{s^n_{m=PV}}$. The formula for the spatial (origin zone to destination zone) and temporal demand for PVs in the current iteration, $s^n_{o,d,t,PV}$, is displayed in Eqn. 4.

$$s^n_{o,d,t,PV} = p^n_{o,d,t,PV} \times D_{odt} \qquad \forall o \in O, \forall d \in D, \forall\, t \in T \tag{4}$$

where D_{odt} denotes the total trip demand from origin zone o to destination zone d departing at time t, which is exogenous to the integrated model system, meaning it is independent of the iteration. Notably, the demand for origin zone o and to destination zone d is based on aggregating traveler agents with origin nodes that are inside origin zone o and destination nodes that are inside destination zone d.

Each traveler agent in the dynamic simulation-based parking assignment model must choose a parking lot, where A is the set of parking lots, indexed by $a \in A$. In this study, each traveler creates an ordered list of parking lot preferences, based on their own expected generalized cost of travel. Each traveler with a PCV drives from their origin to a parking lot before walking from the parking lot to their activity location. Each traveler with a PAV rides from their origin to their activity location (i.e., destination node) after which the vehicle deadheads to a parking lot. Eqn. 5 and 6 display the expected generalized cost functions for PCV travelers and PAV travelers respectively.

$$EC_{PCV,a} = VOT_{trv} \times t_{trv,a} + VOT_{wlk} \times t_{wlk,a} + CPM \times d_a \qquad \forall a \tag{5}$$

$$EC_{PAV} = VOT_{wt} \times t_{wt,a} + CPM \times d \qquad \forall a \tag{6}$$

where VOT_{trv} is the in-vehicle VOT, and $t_{trv,a}$ is the travel time between the origin and parking lot a; VOT_{wlk} is the walking VOT, and $t_{wlk,a}$ is the walking time between parking lot a and the traveler's destination; VOT_{wt} is the waiting VOT, and $t_{wt,a}$ is the length of time the traveler must wait at the activity location to be picked for their return home trip, when their PAV is in parking lot a; CPM is the vehicle's cost per mile, and d_a is the travel distance between the traveler's origin and parking lot a (via the destination in the case of PAVs).

The parking assignment model simulates the movements of PAV and PCV travelers and the vehicles themselves as well as the occupancy of parking lots, in a time-driven simulation. Hence, the simulation captures the current location of travelers, PAVs, and PCVs as well as the current occupancy of all parking lots in the transportation network, every time step, which is denoted $\Delta\tau$ (and equal to six seconds in this study).

Each traveler has an ordered list of parking lots because it is possible that a parking lot is full when the PV arrives at the parking lot entrance in the simulation, in which case the traveler or the traveler's PAV needs to travel to the next parking lot on their ordered list. Of note, this study assumes a traveler only becomes aware of a parking lot's occupancy when they arrive at the parking lot—future studies may assume travelers have full knowledge of parking lot occupancies at all times. Additionally, since travelers can go from parking lot to parking lot in the simulation, the expected costs for a parking lot a, EC_a, in a traveler's ordered list does not reflect the detour travel time and distance that occurs in the simulation. Hence, the ordered list of parking lots for an agent is fixed within the current iteration of the model, i.e., an agent does not update their ordered parking list during a simulation."

In addition to capturing hard capacity constraints at each parking lot in the transportation network, the parking assignment model also captures in-lot parking search time. This is an important model feature for dense urban areas with limited parking supply, as drivers can spend considerable time inside parking lots finding an open parking spot. In this study, the parking time after entering the parking lot (in-lot parking time) depends on the volume to capacity ratio of the parking lot. For example, this study uses a BPR function to reflect the in-lot parking time, expressed as Eqn. 7:

$$t_{prk}(v_a) = t_0 \times \left\{1 + \alpha\left(\frac{v_a}{C_a}\right)^{\beta}\right\} \tag{7}$$

where t_{prk} is the in-lot parking time; v_a is the number of vehicles currently in parking lot a (parking and searching for parking); C_a is the capacity of parking lot a; and α, β, and t_0 are model parameters to be calibrated based on data.

The parking assignment model also captures network IVTT and network walking time. The simulation model assumes both vehicles and pedestrians travel along the shortest network path. The model does not currently capture congestion in the road network, as the assumption is that parking lot capacity is the limiting constraint on PV mode demand. Additionally, the simulation model does not capture congestion or capacity at drop-off points (i.e., activity locations).

As noted in Figure 2, the simulation-based parking assignment model returns the service quality and costs for PV modes. It does so by taking the average values for service quality and cost from all traveler agents with origin o, destination d, departure time t, and PV mode m, as denoted in Eqn. 8.

$$q^{n}_{o,d,t,m,k} = \frac{\sum_{r\in R} \delta^{r,n}_{o,d,t,m}\, q^{r,n}_{k}}{\sum_{r\in R} \delta^{r,n}_{o,d,t,m}} \qquad \begin{array}{c}\forall o \in O, \forall d \in D, \forall t \in T \\ \forall m \in M, \forall\, k \in K_m\end{array} \tag{8}$$

Where, $\delta_{o,d,t,m}^{r}$ is an indicator variable equal to one if agent r has origin o, destination d, departure time t, and was assigned to mode m in iteration n; $q_k^{r,n}$ is agent r's experienced service quality or cost metric k's value in iteration n. The set of experienced service quality or cost metrics K_m, vary by PV mode m. For PCV, K_{PCV} includes IVTT from origin to parking lot, in-lot parking time, parking fee, walking time from/to the parking lot, the opposite direction IVTT, and vehicle travel distance to calculate vehicle parking cost. On the other hand, for PAV, K_{PAV} includes include IVTT from origin to destination, total vehicle travel distance, parking fee, and the waiting time for the PAV to pick up the traveler for the return home trip. The values in Eqn. 8 are then fed into the mode choice model.

4.2.2 Multinomial Logit Mode Choice Model

This section describes the mode choice model. The study employs the random utility maximization framework to model mode choice. The utility function for each mode can be written as Eqns. 9–13:

$$U_{PCV} = \beta_{IVTT,PCV}(t_{trv} + t_{prk}) + \beta_{wlk}t_{wlk} + \beta_{cost}(c_{opr}d + c_{prk}t_{dur}) + \epsilon \tag{9}$$

$$U_{PAV} = \beta_{IVTT,PAV}t_{trv} + \beta_{wt}t_{wt} + \beta_{cost}(c_{opr}d + c_{prk}t_{dur}) + \epsilon \tag{10}$$

$$U_{SCV} = \beta_{SV} + \beta_{IVTT,SCV}t_{trv} + \beta_{wt}t_{wt} + \beta_{cost}c_{fr} + \epsilon \tag{11}$$

$$U_{SAV} = \beta_{SV} + \beta_{IVTT,SAV}t_{trv} + \beta_{wt}t_{wt} + \beta_{cost}c_{fr} + \epsilon \tag{12}$$

$$U_{Transit} = \beta_{Transit} + \beta_{IVTT,Transit}t_{trv} + \beta_{wlk}t_{wlk} + \beta_{wt}t_{wt} + \beta_{cost}c_{fr} + \epsilon \tag{13}$$

where t_{trv} is path travel time (origin to the final parking lot entrance), t_{prk} is in-lot parking time from Eqn. 7, t_{wlk} is walking time, t_{wt} is waiting time, c_{opr} is vehicle operating cost per mile, d is vehicle driving distance (including parking lot searching travel), c_{prk} is parking fee per hour, t_{dur} is parking duration time, c_{fr} is the fare of shared vehicle or transit, β_{SAV} and $\beta_{Transit}$ are mode-specific coefficients, β_{IVTT} is IVTT coefficient, β_{cost} is cost coefficient, and β_{wlk} and β_{wt} are coefficients for each variable.

Among those variables, t_{trv}, t_{prk}, c_{prk}, and d change in the parking assignment model, and the other non-beta parameters and variables remain unchanged based on scenario settings. $\beta_{IVTT,PCV}$, $\beta_{IVTT,PAV}$, β_{wlk}, β_{wt}, and β_{cost} are frequently used variables in the mode choice model and can be found from many studies in the literature. Wardman (*34*) and a TCRP Report (*35*) collect and list relative time valuations for transit travel from decades of studies in UK and US, respectively.

The study also assumes that the error terms, ϵ, are independent (across modes and agents) and identically distributed. Hence, the functional form for mode choice is the multinomial logit model. Given the modal attributes from the previous iteration of the parking assignment model, the exogenous modal attributes and other parameter values, as well as the beta coefficients, determining the mode choice probabilities, $\boldsymbol{p}$, from the multinomial logit model is straightforward and computationally inexpensive.

4.3 Model Output

After the iterative solution approach converges to a solution, there are a variety of system-level and agent-level performance metrics that can be output for analysis purposes. The system-level metrics include VMT, empty VMT, final mode splits, parking lot occupancy and parking lot revenue. The agent-level metrics include travel time, walk time, travel cost, generalized cost, and systematic utility.

5 CASE STUDY

5.1 Network Configuration

This study uses a grid network describing an imaginary central business district (CBD). The network, displayed in Figure 3, has 8 external origin nodes (Nodes 1 to 8), 22 activity locations (Nodes 9 to 30), and 10 in-network parking lots (Nodes 31 to 40) with 1 out-of-network parking lot (Node 41) that accommodates unassigned vehicles. The size of a block is 600 ft by 500 ft and the width of the road is 60 ft. The main road links are unidirectional with a uniform vehicle speed (25 ft/s) and a uniform walking speed (4 ft/s).

Parking assignment requires a fine spatial resolution, particularly in the CBD. Each intersection is divided into four nodes to reflect intersection delays. Each internal short link in each intersection has additional travel times: 12 seconds for the *through* direction and 24 seconds for a left turn and a U-turn. Each activity location and parking lot has two bi-directional links connected with the main road that take 18 seconds to traverse and are accessible only from the adjacent direction links (i.e., only right turn is available) and a short detour (ex: U-turn at the downstream intersection) is required for the opposite direction travel. For example, assume a PAV with external origin 3 and activity location 21 parks in lot 36 in Figure 3, the node sequence of the path would be: [3, 539, 537, 122, 535, 533, 531, 529, 530, 549, 550, 212, 21, 211, 550, 552, 362, 36].

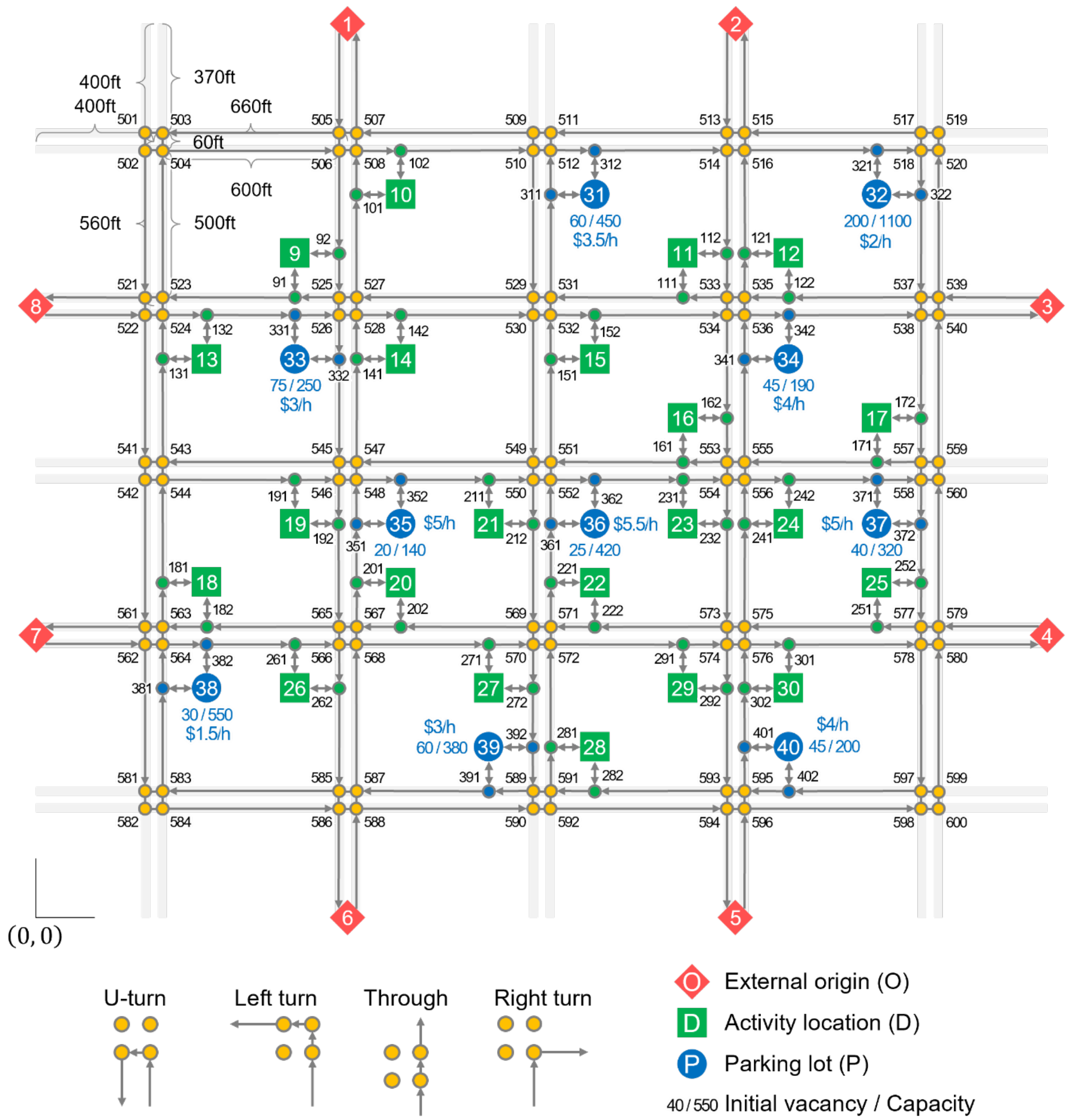

Figure 3 Grid Network for Parking Assignment Simulation

5.2 Trip Generation and Distribution

Vehicle trips are generated every six seconds ($\Delta\tau = 6sec$) and the simulation runs for four hours (i.e., there are 2,400 time steps during the process). To collect enough samples, each simulation runs three times (i.e., three days). There are 12,000 entering trips including PV and non-PV (SV or public transit) users per scenario. To balance the parking location availability throughout the day, 3,000 PVs randomly exit the parking lot during the analysis period. The 12,000 entering trips have uniformly distributed origin and destination nodes (and zones) and departure times. Additionally, the model does not explicitly model travel from activity location or parking lot to external origin. Rather, the study uses fixed values for PAV user pickup wait time and IVTT to external origin. Additionally, the case study assumes that 50% of PAV travelers schedule pickup service and have a zero minute wait time, while the other 50% do not schedule pickup service and wait for their vehicle to travel from parking lot to activity location.

5.3 Parking Lots

Each parking lot has a fixed parking capacity and a fixed parking fee. The total parking capacity across the 10 parking lots is 4,000 and 15% of parking spots (600) are vacant at the beginning in the base scenario. The results section includes scenario analyses with respect to changes in parking fees and parking lot capacities. Parking fees range from \$1.5/h to \$5.5/h with mean (median) values of \$3.65/h (\$3.75/h). Parking lot fees are based on lots in major cities in Germany and the United States (*36*). When all parking lots are full, vehicle must go to the out-of-network parking lot (Lot 41) that is 0.5 miles away, costs \$5.5/h, and has a capacity of 10,000.

For the in-lot parking space search time function (Eqn. 7), the study uses the following parameter values for all parking lots: $t_0 = 1$ minute and $\alpha = \beta = 2$. According to the function, parking time is 60 seconds when the parking lot is empty, 90 seconds at 50% vacancy, 120 seconds at 30% vacancy, and 180 seconds at 1% vacancy.

5.4 Model Parameters and Values of Time

The model parameters and VOTs used in this study are based on those in Kolarova et al. (*3*). Since there is no experience of AV travel yet, the value of AV travel time in most studies relies on SP survey or assumptions. The San Diego Association of Governments (SANDAG) multiplies 0.75 from the PCV in-vehicle VOT as a modifier considering the improved convenience (*37*), which is as same as Correia et al. (*38*). Conversely, Kolarova et al. estimate that in-vehicle VOT in PAVs is 0.64 of in-vehicle VOT in PCVs. According to a review paper by Singleton, several simulation studies assume various VOTs of AVs, and the value ranges from 0% to 100% of PCV VOT (*39*). This study applies Kolarova et al.'s survey-based number in the base scenario and adjusts the number in alternative scenarios with different modifiers. Note that Kolarova et al.'s SAV refers to "driverless taxi" in their survey. The coefficient values used in this study are shown in Table 2.

Table 2 Model Parameters

Variable		PCV	PAV	SCV	SAV	Transit
Mode-specific constant		0	0	-0.927	-0.927	-3.23
Time-related	In-vehicle time (minutes)	-0.0966	-0.0621	-0.11	-0.103	-0.0577
	Walking time (minutes)	-0.142	-	-	-	-0.031
	Waiting time (minutes)	-	-0.112	-0.112	-0.112	-0.088
Cost-related	Operating cost and parking fee (USD)	-0.709	-0.709	-	-	-
	Fare (USD)	-	-	-0.709	-0.709	-0.709

5.5 Travel Costs for Mode Choice

The mode choice model includes out-of-network IVTT since the mode choice is not only based on the travel in the simulated network, but also affected by the whole travel path. For each traveler, the out-of-network IVTT time for two directions are added to the in-network IVTTs (including the parking lot searching time) determined by the parking assignment model. PV and SAV users' out-of-network IVTT is set to 20 minutes per one way, and transit users' out-of-network IVTT is set to 30 minutes per one way. Including the in-network IVTT, the total IVTT becomes around the US average (27.6 minutes for one-way commute) according to recent data (*40*). Assuming the average speed is 24 mi/h, the out-of-network one-way travel distance is 8 miles.

This study assumes 10 minutes (5 minutes in each direction) of waiting time for SAV and 20 (10+10) minutes of waiting time and 10 (5+5) minutes of walking time for transit. Transit fare is \$5 (thus, \$10 for the two-way trips). Uber fare consists of base fare ($2), cost per minute ($0.4/min), and cost per mile ($1/mi) (*41*), which can be changed when the company starts to run AVs. For SAVs, Chen and Kockelman use $0.75–1/mi (*42*), Kaddoura et al. assume $0.64–0.84/mi (€0.35–0.46/km) (*43*), and An et al. estimate $0.66/min (*44*), which is a simplified cost estimation of the current Uber service. Considering those studies, this study uses $1.6/mi for SCV fare and $0.8/mi for SAV fare.

5.6 Scenarios

This study analyzes several scenarios that reflect various possible future conditions at different points in time. Table 3 displays the full set of scenarios. In the base scenario, all PVs are PCVs. Those PCVs are all converted into PAVs in Scenario A. Scenarios B1 and B2 are all PAV scenarios, but they apply different in-vehicle VOTs for PAV, 50% and 90% of PCV in-vehicle VOT, respectively. Scenarios C1 and C2 are also all PAV but uniformly apply $3.5/h fee to all parking lots, and Scenario C2 additionally attempts to evenly distribute parking lot capacity across the network. Table 4 displays the parking lot fees, capacity, and initial vacancy across a variety of scenarios.

In the base scenario and Scenarios A–C2, the traveler agents are aggregated into a single origin zone and single destination zone for the mode choice model. However, in Scenarios D1–D5, the traveler agents are aggregated into four destination zones in the mode choice model. Scenarios D1 through D5 vary the proportion of PVs that are PAVS, as opposed to PCVs, between 0 and 1 in increments of 0.25.

Table 3 Scenarios

<table>
<tr><th>Scenario</th><th>Modes</th><th>PAV VoT</th><th>Parking fee</th><th>Parking lot capacity</th><th>PAV percentage</th><th>Description</th></tr>
<tr><td colspan="7">One Origin and One Destination Spatial Aggregation in Mode Choice</td></tr>
<tr><td>Base</td><td>PCV, SCV, Transit</td><td>-</td><td>Varied</td><td>Uneven</td><td>0%</td><td>CV default</td></tr>
<tr><td>A</td><td>PAV, SAV, Transit</td><td>64.3% of PCV</td><td>Varied</td><td>Uneven</td><td>100%</td><td>AV default</td></tr>
<tr><td>B1</td><td>PAV, SAV, Transit</td><td>90.0% of PCV</td><td>Varied</td><td>Uneven</td><td>100%</td><td rowspan="2">Variations in PAV VoT parameter</td></tr>
<tr><td>B2</td><td>PAV, SAV, Transit</td><td>50.0% of PCV</td><td>Varied</td><td>Uneven</td><td>100%</td></tr>
<tr><td>C1</td><td>PAV, SAV, Transit</td><td>64.3% of PCV</td><td>Uniform</td><td>Uneven</td><td>100%</td><td rowspan="2">Variations in cost variable</td></tr>
<tr><td>C2</td><td>PAV, SAV, Transit</td><td>64.3% of PCV</td><td>Uniform</td><td>Even</td><td>100%</td></tr>
<tr><td colspan="7">One Origin and Four Destinations Spatial Aggregation in Mode Choice</td></tr>
<tr><td>D1</td><td>PCV, SCV, Transit</td><td rowspan="5">64.3% of PCV</td><td rowspan="5">Varied</td><td rowspan="5">Uneven</td><td>0%</td><td rowspan="5">Variations in PAV Ownership Percentage</td></tr>
<tr><td>D2</td><td>PCV, PAV, SCV, SAV, Transit</td><td>25%</td></tr>
<tr><td>D3</td><td>PCV, PAV, SCV, SAV, Transit</td><td>50%</td></tr>
<tr><td>D4</td><td>PCV, PAV, SCV, SAV, Transit</td><td>75%</td></tr>
<tr><td>D5</td><td>PCV, PAV, SCV, SAV, Transit</td><td>100%</td></tr>
</table>

Table 4 Parking Lot Information across Scenarios

Parking lot	Default			Scenarios C1 and C2	Scenario C2	
	Parking fee (USD/h)	Capacity (veh)	Initial vacancy (veh)	Parking fee (USD/h)	Capacity (veh)	Initial vacancy (veh)
31	3.5	450	60	3.5	250	38
32	2	1,100	200	3.5	250	37
33	3	250	75	3.5	750	112
34	4	190	45	3.5	400	60
35	5	140	20	3.5	500	75
36	5.5	420	25	3.5	550	83
37	5	320	40	3.5	350	52
38	1.5	550	30	3.5	300	45
39	3	380	60	3.5	300	45
40	4	200	45	3.5	350	53
41	5.5	10,000	10,000	5.5	10,000	10,000

6 RESULTS

6.1 No Spatial Disaggregation Scenarios

The Solution Approach section and Figure 2 describe an iterative solution approach to solve the fixed-point integrated mode choice and parking location choice problem, $\boldsymbol{p} = f_m\left(f_p(\boldsymbol{p})\right)$. However, when the variable p is a scalar or low-dimensional vector, and the function $f_m\left(f_p(\boldsymbol{p})\right)$ is relatively easy to evaluate, it is possible to use enumeration to solve the fixed point problem. The base scenario and scenarios A through C2 meet these criteria because the mode choice model does not include any spatial or temporal disaggregation; hence, the dimension of $\boldsymbol{p}$ is $1 \times 1 \times 1 \times |M|$. Using an enumeration method also has the added benefit of ensuring that all fixed points are identified, whereas the iterative solution approach may not identify all possible fixed points solutions.

Figure 4 shows the results of the enumeration approach for the base scenario and scenarios A through C2. The x-axis displays the input values for the PV mode share, $p_{m=PV}$. and the y-axis displays the evaluation of the integrated parking assignment and mode choice function, $f_m\left(f_p(p_{m=PV})\right)$. Values along the diagonal represent solutions to the fixed point problem.

Using an increment of 1%, Figure 4 shows that there is a unique solution for the base scenario and scenarios A through C2. Unsurprisingly, the lines are all downward sloping. Moreover, the relative flatness of Scenario C1 and C2 likely stems from the fact that the parking fees across the network are uniform. The existence and uniqueness of a solution for all scenarios engenders a straightforward analysis of the fixed points solutions across scenarios.

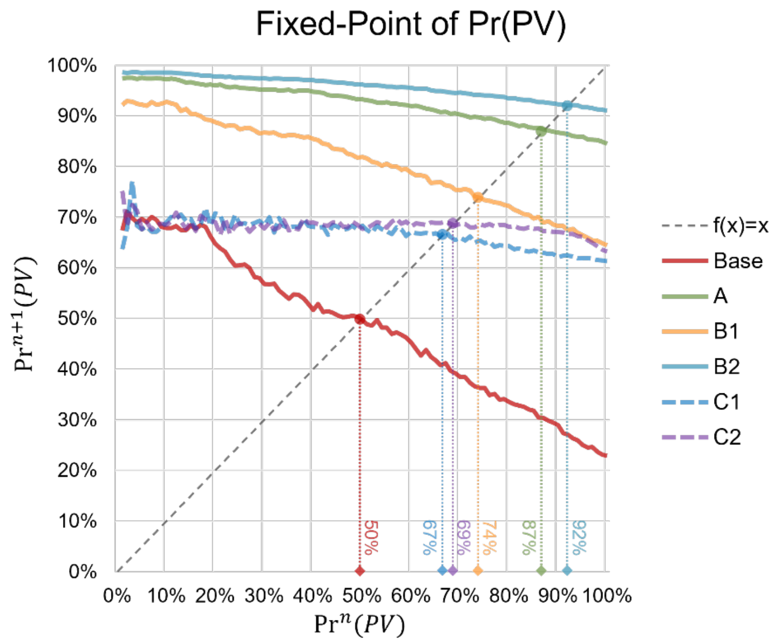

Figure 4 Fixed Points of Pr(PV)s

6.1.1 Mode Share Metrics

Figure 5 shows the mode shares for all modes in each scenario. The mode share for PV is lowest in the base scenario where the PVs are PCVs, and the mode share is 50%. In Scenario A, where all PVs are PAVs, PV mode share significantly increases to 87% due to eliminating walking time, potentially reducing parking fees, and the reduction in IVTT disutility.

In Scenario B2, the assumption is that PAV in-vehicle VOT is 50% of PCV in-vehicle VOT, and the PAV mode share increases all the way to 92%. In Scenario B1, when PAV in-vehicle VOT is 90% of PCV in-vehicle VOT, the PAV mode share is 74%. Taken together, Scenario A, B1, and B2 unsurprisingly indicate that PAV IVTT disutility has a significant impact on mode share.

The properties of parking lots also affect the choice probability. Instead of the varied parking fees that range from \$1.5/h to \$5.5/h in the base scenario, all parking fees are set to \$3.5/h in Scenarios C1 and C2. In addition, Scenario C2 redistributes the parking lot capacities to be more evenly distributed in the network. In Scenarios C1 and C2, the PAV mode shares are 67% and 69%, respectively. This represents a notable reduction in mode share compared to Scenario A, in which the larger parking lots had lower fees.

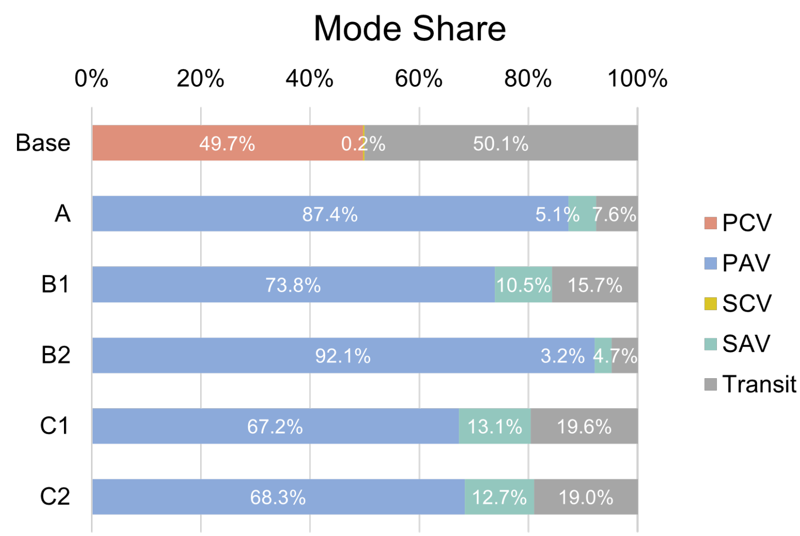

Figure 5 Mode Share by Scenarios

6.1.2 VMT Metrics

In addition to the increase of the travel demand (Figure 6a), total PV VMT substantially increases in PAV scenarios (Figure 6b). Note that we only consider in-network VMT (starting from external origin nodes), and do not include the VMT from the actual origin to external nodes. Total VMT increases by 15,000–22,000 miles in Scenarios A, B1, and B2 compared to the base scenario. On the other hand, the increases are reduced when there is no difference in parking fees in Scenario C1 and C2. The VMT increase is controlled better when the parking lot capacity is evenly distributed across space.

As shown in Table 5 and Figure 6c, the average VMT for a PCV is 1.07 miles in the base scenario, and the average VMT for a PAV stretches from 1.18 miles to 2.57 miles in the other scenarios. The VMT per vehicle increases 1.38–1.51 mi/veh in default parking lot settings compared to the base scenario. In Scenarios C1 and C2, VMT per vehicle increases are only 0.11–0.35 mi/veh. This clearly indicates that the spatial distribution of parking prices and parking supply have a significant impact on average VMT per vehicle. Hence, if policymakers and planners are interested in reducing VMT in a future era with PAVs, parking supply and pricing must be considered alongside other policy measures.

The increase in total network VMT from PAVs shown in Figure 6b stems from both an increase in PV trips (shown in Figure 6a) and an increase in network VMT per vehicle (shown in Figure 6c). Hence, VMT in a future with AVs is likely to increase due to travelers switching to PV and also driving more miles in PAVs than they did or would have in PCVs. Policymakers interested in decreasing VMT will likely need a multi-pronged approach to address these two factors that are expected to increase VMT.

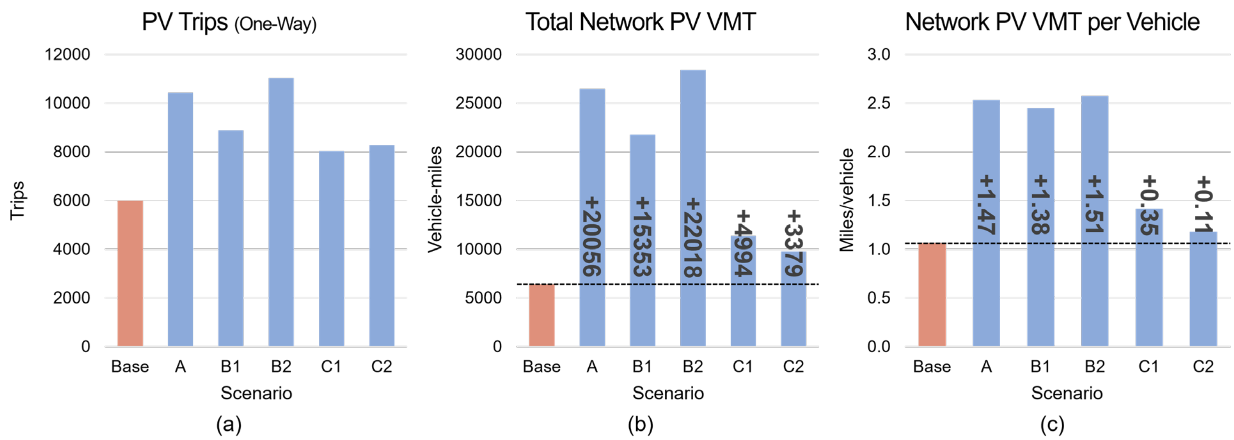

Figure 6 PV's VMT in the Network: (a) Number of PV Trips, (b) Total PV VMT, and (c) VMT per Vehicle

6.1.3 Travel Time and Travel Cost Metrics

Table 5 shows the average travel time components for travelers along several dimensions, along with average total travel time, and average travel distance. Travel distance is the distance in the grid network (counted from the external origin node) and includes the deadheading travel distance. The travel distance in every PAV scenario is longer than the distance in the PCV base scenario.

Since PCV travelers need to travel to parking lots and search for parking, while PAV travelers do not, the average IVTT of PCV travelers is 3.3 minutes longer than that of PAV travelers on average. On the other hand, PAVs spend more time searching for parking than PCVs. The reasons are twofold; first there are more vehicles in the PAV scenarios and second PAVs have more homogeneous parking lot preferences—they want cheap parking and do not care much about distance from activity location nor parking spot search time—making cheaper parking lots more crowded.

The PCV users' average (one-way) walking time from parking lot to activity location is about 6 minutes in one direction, and nearly 13 minutes total including the activity location to parking lot return walk. Of course, walking time is zero minutes for the PAV scenarios. The average waiting time for PAVs to pick up PAV users is 1.2-2.4 minutes in Table 5. The variation across scenarios comes from the distance between parking lots and activity locations.

The final column sums average traveler IVTT, walking time, and waiting time to determine total travel time. The results show that the total roundtrip in-network travel time for PCV is significantly higher than total roundtrip in-network travel time for PAV users. Hence, there are significant time benefits associated with PAVs compared with PCVs.

Table 5 Average PV Traveler Distances and Times

Scenario	Number of PVs (veh)	Travel distance (mi/veh)	In-lot parking time (min/veh)	IVTT (min/prs)	Walking time (min/prs)	Waiting time (min/prs)	Total time (min/prs)
Base	6,000	1.07	2.45	8.19	12.73	-	20.9
A	10,440	2.53	2.71	4.83	-	2.37	7.2
B1	8,880	2.45	2.70	4.83	-	2.40	7.2
B2	11,040	2.57	2.72	4.84	-	2.35	7.2
C1	8,040	1.42	2.61	4.84	-	1.39	6.2
C2	8,280	1.18	2.45	4.85	-	1.22	6.1

Table 6 presents an even more holistic comparison of the travel experiences of PV users across scenarios; it includes average monetary costs and monetized travel time components based on the values of IVTT, walking time, and waiting time in the mode choice model. The final column of Table 6 displays the total generalized cost per traveler.

Table 6 shows that the in-network vehicle operating cost is \$0.06 to \$0.75 for PAVs than PCVs, depending on the scenario. This result stems from the deadheading distance that PAVs travel after dropping off travelers at their activity locations.

Scenarios A, B1, and B2 have higher average parking fees for travelers compared with the base scenario. Hence, despite PAVs being able to travel further to cheap parking lots, the increase in total PV demand in the PAV scenarios forces some travelers to pay for parking at the high-cost parking lots, which more than offsets their ability to access cheap parking lots. Since the parking fees are unified in Scenarios C1 and C2, the popular cheaper-than-average parking lots are not cheap anymore. Thus, the average parking fee increases in those scenarios.

The monetized IVTT, monetized walking time, and monetized waiting time columns of Table 6 parallel the IVTT, walking, and waiting time columns in Table 5. IVTT is higher and walking time is significantly higher for PCVs than PAVs, while waiting time is higher for PAVs.

The final column of Table 6 is the sum of all the cost and monetized cost components in the preceding columns. Interestingly, while Scenario A and B1 have the lowest total generalized costs, the base scenario has a lower generalized cost than Scenarios C1 and C2. This latter finding stems directly from the high parking cost per person in Scenarios C1 and C2.

Table 6 Average Monetized Traveler Costs

Scenario	Vehicle operating cost (USD/prs)	Parking fee (USD/prs)	Monetized IVTT (USD/prs)	Monetized Walking time (USD/prs)	Monetized Waiting time (USD/prs)	Total generalized cost (USD/prs)
Base	0.53	4.72	1.12	2.55	0	8.92
A	1.27 (+0.73)	5.34 (+0.62)	0.42 (-0.69)	0 (-2.55)	0.37 (+0.37)	7.40
B1	1.22 (+0.69)	5.07 (+0.35)	0.42 (-0.69)	0 (-2.55)	0.38 (+0.38)	7.10
B2	1.29 (+0.75)	5.46 (+0.74)	0.42 (-0.69)	0 (-2.55)	0.37 (+0.37)	7.54
C1	0.71 (+0.18)	7.77 (+3.05)	0.42 (-0.69)	0 (-2.55)	0.22 (+0.22)	9.12
C2	0.59 (+0.06)	7.84 (+3.12)	0.42 (-0.69)	0 (-2.55)	0.19 (+0.19)	9.05

Together with the VMT results, Table 5 and Table 6 illustrates some trade-offs between PCVs and PAVs in terms of travel time, travel cost, and VMT. Compared with the base scenario, the PAV scenarios A, B1, and B2 significantly increase VMT, while reducing average traveler in-network time considerably and slightly reducing traveler generalized costs. On the other hand, compared with the base scenario, the PAV scenarios C1 and C2, only slightly increase VMT, while significantly reducing average in-network travel time. However, C1 and C2 have a higher total generalized cost than the baseline scenario because of the higher parking costs that are needed to reduce VMT.

6.1.4 Vehicle Hours Traveled vs. Traveler In-vehicle Travel Time Results

Figure 7 displays both total vehicle hours traveled (VHT) and total traveler IVTT under the various scenarios. Figure 7a displays the total VHT for PVs and traveler IVTT. Even though the number of travelers and VHT increase in the PAV scenarios, there is no significant increase in total traveler IVTT. Understandably, this is because the PAVs are empty during the parking search process. Figure 7b shows that PV VHT per vehicle increases in Scenarios A, B1, and B2 relative to the baseline scenario; conversely, PV VHT per vehicle only increase slightly in Scenario C1, while Scenario C2 shows a slight decrease. Figure 7c displays the average IVTT per traveler, with the main result being that IVTT per traveler is lower in the PAV cases than the baseline PCV scenario. The results in Figure 7c partially explain the increase in PV mode share in the PAV scenarios despite the increase in VHT with PAVs.

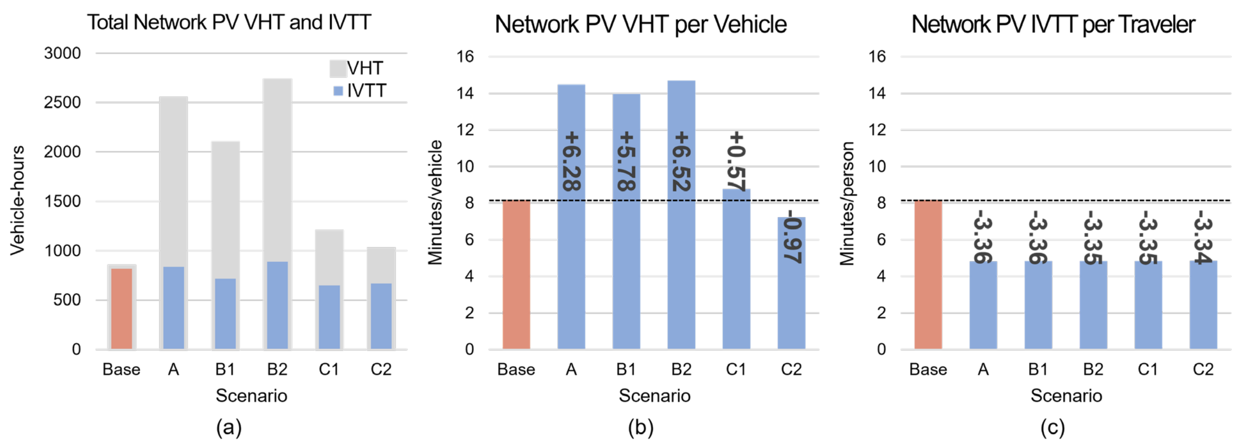

Figure 7 PV's VHT and IVTT in the Network: (a) Total PV VHT and IVTT, (b) VHT per Vehicle, and (c) IVTT per Traveler

6.1.5 Impact of Increased Shared Autonomous Vehicle

According to Balding et al. and Conway et al., using data from the 2017 national household travel survey (*45*), the share of for-hire vehicles (taxi and TNC) is around 0.5% across the country and up to 1.7% in San Francisco and 1.5% in Washington DC (*33*, *46*). Since this study only considers travelers who have their own vehicles, the base scenario (PCV-SCV) shows an even lower mode share for SVs, 0.2%. However, the percentage is much higher in the PAV-SAV scenarios as the SV's travel cost per mile decreases significantly.

Naturally SV, particularly SAVs, impact total network VMT in addition to PAVs. Assuming 40% deadheading miles for SVs (*13*, *33*), SV travel adds 0.67 deadhead miles per in-service mile. Figure 8 illustrates the impact of SAVs on VMT. Figure 8a displays the number of SV trips across the scenarios. Interestingly, Scenarios C1 and C2 produce the highest number of SV trips. Figure 8b displays the total SV deadheading VMT, which parallels the results in Figure 8a. Figure 8c displays the total SV and PV VMT and finds that VMT increases substantially (5,000–22,000 miles, depending on the scenario) in the AV-based scenarios. However, the impact of SV VMT (green bars in Figure 8c) is relatively small compared to PV VMT (blue bars in Figure 8c) in nearly all scenarios.

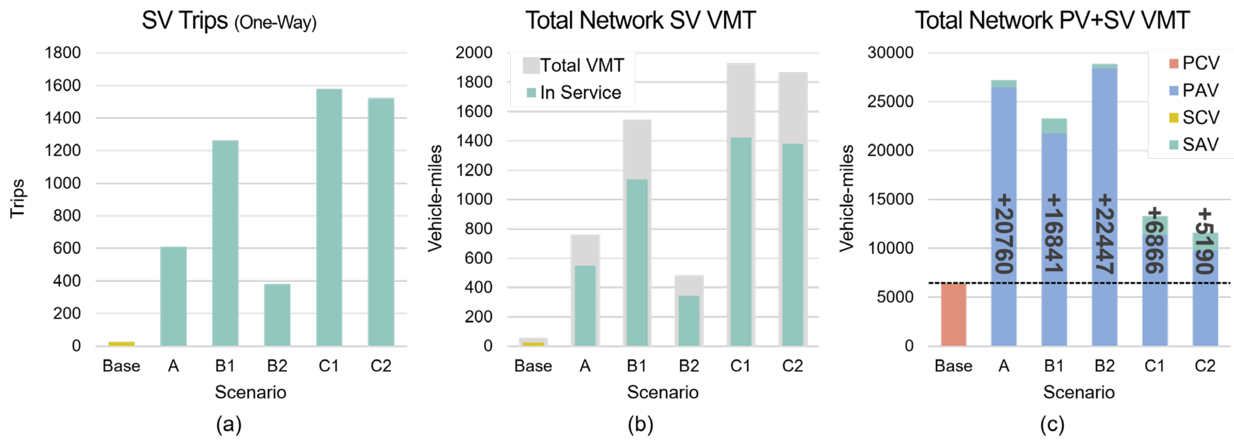

Figure 8 SV VMT in the Network: (a) Number of SV Trips, (b) Total SV Deadheading VMT, and (c) Total PV and SV VMT

6.2 Spatial Disaggregation Scenarios

While the results in the prior subsection were based on an enumeration-based solution approach to the integrated mode choice and parking assignment problem, this section presents results using the iterative solution approach proposed in the Solution Approach section. Notably, the iterative solution approach is necessary in this section because the mode choice model aggregates the travelers into four destination zones, rather than just one destination zone like in the prior subsection. This subsection illustrates the ability of the iterative solution approach to identify a solution to the fixed-point problem.

Figure 9 displays the mode choice results under a variety of different scenarios. The parameter α denotes the proportion of travelers who own a PAV, as opposed to a PCV. Each row of graphs in Figure 9 denotes a separate α value, whereas α does not vary across columns. The figure varies α between 0 and 1 in increments of 0.25. Each column in Figure 9 denotes a separate initial starting point for PV mode choice in order to determine if the iterative solution algorithm finds different fixed points as a function of the initial starting points.

The lines in each of the 15 graphs in Figure 9 indicate that the iterative solution approach converges to a fixed-point solution under all cases after less than 20 iterations. Moreover, given that the only thing that changes between the three graphs in each row is the initial starting point of PV mode choice, the 15 graphs indicate that the iterative solution approach finds the same fixed point, independent of starting point of the mode choice probabilities. The analysis below assumes a single fixed-point solution based on the empirical finding in Figure 9 that the algorithm converges to a single fixed point. However, it is important to note that this paper does not prove the model system always admits a unique solution.

The results in Figure 9 indicate that PAV owners are much more likely to choose PV than PCV owners, in all scenarios. However, an interesting finding is that as the proportion of travelers who own a PAV, α, increases, the mode choice probabilities for PAV owners decrease, while they increase for PCV owners. The reason for this stems from the fact that PAV and PCV owners prefer different parking lots. PCV owners are highly sensitive to the distance between a parking lot and their activity location, whereas PAV owners are not. This means that as the proportion of travelers owning a PAV increases, PAV owners must compete with more travelers who share their parking lot preferences (i.e., PAV owners who mainly care about price), while PCV owners compete with fewer travelers who share their parking lot preferences (i.e., PCV owners who are sensitive to walking distance in addition to price).

This logic also explains why the range of modal splits for PCV owners across zones narrows as α increases. When α is zero, the range of PV mode share across zones is as wide as 15%, indicating that PCV travelers going to a zone with congested parking lots and high parking costs are significantly less likely to choose PV than travelers going to zones with uncongested and lower cost parking lots. Conversely, the range of PAV mode shares across zones is quite small under all scenarios, because a traveler's destination does not heavily impact where they prefer to and do park their PAV.

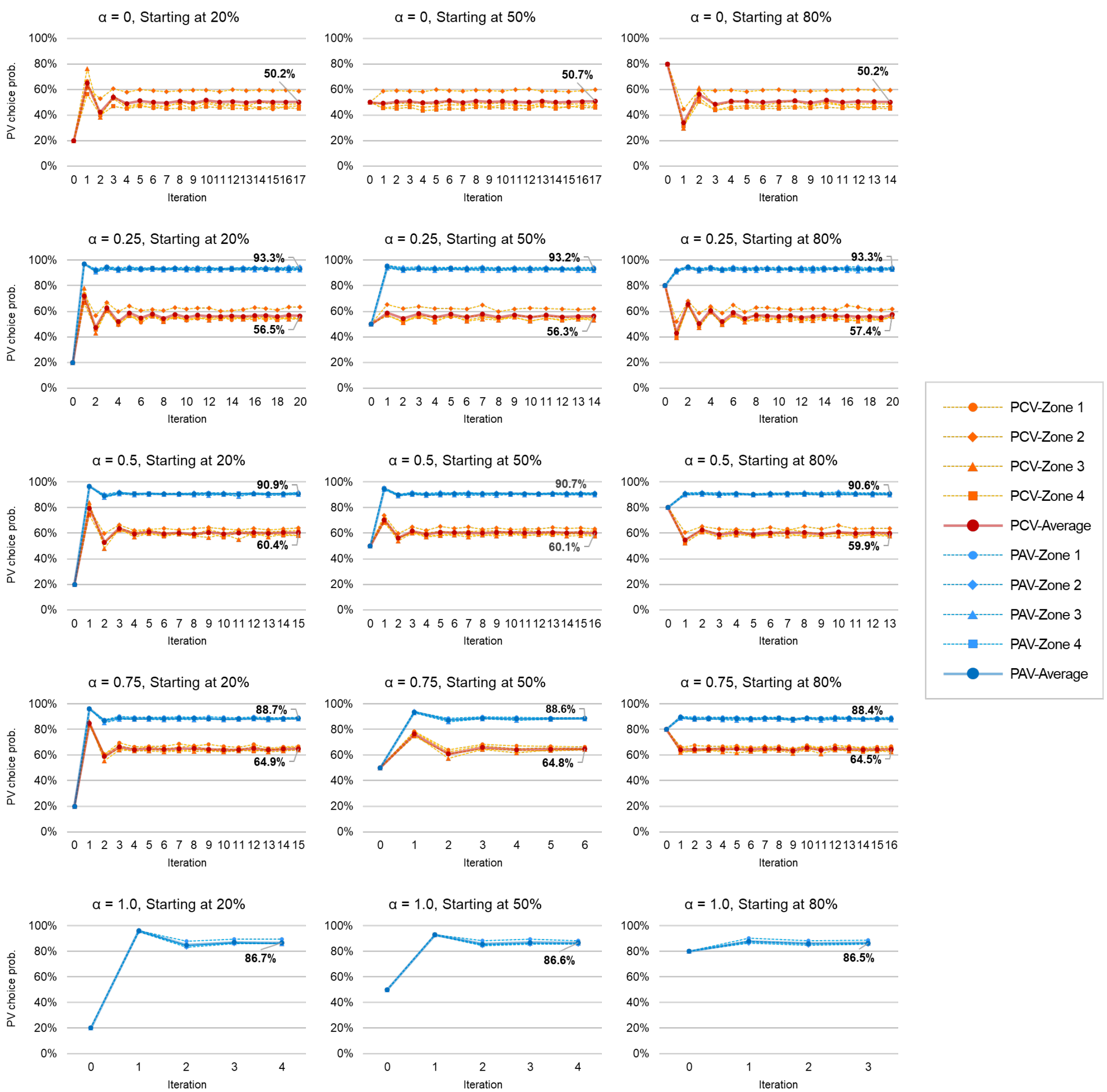

Figure 9 Mode Choice Convergence Plots Varying PV Mode Share Starting Points by Column from 20% to 80%, and PAV Ownership Proportion by Row from 0.0 to 1.0

7 DISCUSSION

Although the case study presented in this paper is based on a fictional CBD, the results section hopefully illustrates the power of the integrated mode choice and parking location choice model to provide valuable, transferrable, and generalizable insights into VMT, parking occupancy, transportation system performance and user costs and travel times in a future with PAVs and PCVs. Moreover, the model can be applied to any region as long as detailed data about the road network, parking lots, and travel demand (or trips) are available. The proposed solution approach, incorporating the simulation-based parking assignment model and the multinomial logit mode choice model, are computationally efficient and would easily scale to large metropolitan areas given data availability.

The proposed model should also be quite useful for policy and planning analysis and decision support. For example, compared to the current PCV-only case, redistributing parking spaces appears able to prevent dramatic increases in VMT while not reducing PV mode share in a future with PAVs. This suggests the spatial distribution of parking supply and parking pricing can significantly impact VMT in the future with PAVs.

Moreover, although not shown explicitly in the results section, the model can demonstrate, under certain scenarios, that parking pricing alone may struggle to reduce VMT and PV demand. Rather, joint parking pricing and roadway pricing is likely necessary in an AV future to reduce VMT and PV demand.

Another implicit finding from this study is that PAVs searching for parking would often look for the cheapest possible lot in the area, particularly when the driving cost per mile is low. Hence, if all PAVs want to access the same cheap lot(s) in the periphery of the CBD, this/these lot(s) will become full, and the other PAVs will need to search for and drive to the next cheapest lot. This finding has important technology, policy, and modeling implications. From a technology standpoint, providing accurate real-time information to travelers and/or PAVs about parking lot occupancy could be quite useful. From a policy standpoint, setting parking prices based on disaggregate spatial resolutions in CBDs may not be helpful in a world of PAVs. Moreover, there is clearly a value in promoting a reservation system of parking lots and even spaces in parking lots to reduce both parking lot search time and parking space search time, respectively. Finally, from a modeling standpoint, a future extension involves incorporating traveler/PAV knowledge of parking lot occupancy into the modeling framework to analyze the benefits of this information on VMT.

Another future modeling extension involves incorporating roadway congestion into the modeling framework. The results in this paper clearly indicate a significant increase in roadway VMT as a result of the attractive attributes of PAVs as well as the increase in parking search distance for PAVs. However, at some point, if enough vehicles are driving around searching for the cheapest parking lot with available space, the network is going to experience congestion. This increase in congestion would normally have a leveling effect on parking search costs, as human drivers would perceive the time costs of sitting in congestion and likely choose more expensive parking locations and leave the roadway network. However, if the vehicles searching for a cheap parking spot are driverless, they will have much lower costs per minute in congestion and are much less likely to choose nearby parking lots and exit the roadway network. This is a particularly troubling insight for cities in the future. It suggests that congestion pricing in cities may become even more vital to prevent gridlock and vehicles may need to be charged not just per mile but per minute on the road network in order to avoid regular gridlock in CBDs.

A related future model extension includes incorporating congestion and capacity constraints at pickup and drop-off spots near activity locations in dense urban areas. With a large percentage of PAVs and/or SAVs in a dense urban area, large queues are likely to build at pickup and drop-off points associated with activity locations with high demand, such as large office buildings. These queues may even spillover into the roadway network; thereby requiring a response for traffic managers, planners, or regulators.

A final research area includes conducting stated preference surveys to better estimate model parameters used in this study. Parameters associated with willingness-to-pay, willingness-to-wait, and willingness-to-walk are likely to have a significant impact on model results related to mode share and VMT.

8 CONCLUSION

Modeling, understanding, and forecasting the potential implications of AVs and PAVs on travel behavior, travel demand, and transportation systems under a variety of possible future scenarios is critical in terms of planning for AVs. This study focuses on the potential transportation system implications during the transition from PCVs to PAVs for near-activity travel in urban areas. Specifically, given the ability of PAVs to drop-off travelers at their activity location and then deadhead to a parking location, under certain assumptions it is conceivable that PAVs will drive far distances to park and/or drive around looking for an open parking space. This process would significantly increase VMT compared to PCVs that drive directly to a parking location close to the traveler's activity location.

To analyze the impacts of PAVs on near-activity location travel, parking lot usage, overall VMT, and traveler cost and travel time this study proposes an integrated parking assignment and mode choice modeling framework. The proposed mode choice model form is multinomial logit, while the parking model is a dynamic simulation-based model of the temporal dynamics of supply and demand for a system of urban parking locations. The study also proposes an iterative solution approach to solve the integrated mode choice and parking assignment problem. In the iterative solution approach, the parking simulation model calculates system performance and costs for travelers based on the demand for each mode—determined either by the mode choice model or the initial modal splits—while the mode choice model returns modal splits based on the travel costs from the parking simulation model.

The study applies the integrated model and iterative solution approach to an illustrative CBD network. The model results indicate that PAVs significantly increase VMT compared to PCVs. The reason for this result stems from the differential between parking prices and driving fees in the case study. As such, PAVs do not simply look at the stations nearby their traveler's activity location, instead they consider all parking locations and are highly price sensitive. Moreover, in the case where a few parking locations are particularly attractive to PAVs, these parking locations may reach capacity, requiring PAVs to detour and search for other parking locations, thereby further increasing VMT in dense urban areas. The results section also illustrates that PAVs significantly reduce in-vehicle travel time, eliminate walking time, but require travelers to wait a few minutes to be picked up.

The proposed modeling framework can provide valuable insights to researchers, planners, policymakers, and other city officials in terms of the potential implications of AVs on VMT, parking lot usage, mode share, and other measures of transportation system performance and user costs.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Y. Bahk and M. Hyland; simulation for parking assignments: S. An and Y. Bahk; analysis and interpretation of results: Y. Bahk, M. Hyland, and S. An; draft manuscript preparation: Y. Bahk and M. Hyland. All authors reviewed the results and approved the final version of the manuscript.

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