Case Study

Preparing Urban Curbside for Increasing Mobility-on-Demand Using Data-Driven Agent-Based Simulation: Case Study of City of Gainesville, Florida

Yan Wang, Ph.D., A.M.ASCE[1]; Haiyan Hao, S.M.ASCE[2]; and Chen Wang, Ph.D.[3]

Abstract: Cities in many countries are witnessing an era of transformative innovations in vehicular technologies and mobility-on-demand (MoD) services in the context of global initiatives of smart and connected cities. However, advances in the built environment where vehicles operate have not maintained the same pace. The new MoD especially burdens curb environments in urban cores due to competition for spaces for pick-ups and drop-offs (PUDO). These uncoordinated and diverse uses without data-driven management have led to increased safety and sustainability issues. This research intends to address the increasing curbside uses of PUDO activities due to MoD services and proposes a data-driven agent-based simulation approach to plan designated PUDO zones in limited public curbside spaces. A case study was conducted for five street blocks in urban cores of the City of Gainesville, Florida, United States, based on longitudinal parking transaction and violation records, place visitation data, and geospatial data of parking assets. The results show that temporary PUDO zones should be designated at all investigated blocks during peak hours even when the MoD market penetration rate is low (i.e., 10%), which helps mitigate the occurrences of *competing use events*, while permanent PUDO zones should be designated for the two busiest blocks when the MoD market penetration rates increase to 30% or 50%. Sensitivity analyses suggest that the designated PUDO zones can mitigate curbside stresses more effectively when regulating MoD users' PUDO dwell time (e.g., within one minute). This research aims to contribute to data-driven public asset managerial decision-making and strategies in smart cities and benefits more accessible and sustainable living environments in urban cores. **DOI: 10.1061/(ASCE)ME.1943-5479.0001021.** *© 2022 American Society of Civil Engineers.*

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Introduction

The global initiatives of building smart and connected communities have yielded an array of Information and Communication Technology (ICT) and Internet of Things (IoT) applications for more sustainable, livable, and accessible built environments (Francisco et al. 2020). These technologies have revolutionized the way people live, work, entertain, and socialize in cities. However, many outdated urban built environments and infrastructure systems have not kept pace with these rapid technological advancements, which may fail to accommodate people's new living and mobility behaviors. For example, with the increasing popularity of varied mobility-on-demand (MoD) services is the burden imposed on curbside spaces. Conventionally, curbs are used to separate pedestrian activities from vehicular traffic and serve as the frontage for people to switch transportation tools or access roadside properties (Marsden et al. 2020; ITF 2018). The emergence of various MoD services causes different user groups to compete for curbside space uses. Curbs are now places for MoD platforms to place their facilities (e.g., shared bikes, e-scooters, and vehicles), MoD clients to complete transactions, deliverymen to wait and retrieve goods/food, and ride-hailing drivers to load/unload passengers in addition to the conventional functions. These more intense and diversified curbside activities can lead to misuse and oversubscription of curb spaces that negatively impact street traffic, curbside business, urban aesthetics, and pedestrian safety and comfort (NACTO 2013).

Pressured curbside spaces can be further burdened by the increasing MoD market penetration and the adoption of emerging vehicular technologies, such as shared autonomous vehicles (SAVs) (Mckinsey Center for Future Mobility n.d.; ITF 2018). MoD is likely to lead to more curbside pick-up drop-off (PUDO) activities that increase the short-term parking needs while the deployment of SAVs encourages more shared mobility and coordinated mobility services. These trends result in fewer needs for on- and off-street parking, but demand more curbside spaces used for frequent PUDO activities (USDOT 2018; Zhang et al. 2020). PUDO may compete with other curb uses such as private vehicles for curbside parking spaces, especially in urban cores where the most populous places are located. In this regard, it is important to ensure that automated vehicles and emerging mobility services can be safely and effectively integrated into the management of existing curb environments, alongside conventional private vehicles, and other curb space users (USDOT 2018).

Diverse and uncoordinated curb uses may lead to increased congestion (Weinberger et al. 2020), safety issues (Dumbaugh and Li 2010), and transportation-related greenhouse gas (GHG) emissions (Zhang and Batterman 2013; Aftab et al. 2020), which demands

[1]Assistant Professor, Dept. of Urban and Regional Planning and Florida Institute for Built Environment Resilience, Univ. of Florida, P.O. Box 115706, Gainesville, FL 32611 (corresponding author). ORCID: https://orcid.org/0000-0002-3946-9418. Email: yanw@ufl.edu

[2]Ph.D. Candidate, Dept. of Urban and Regional Planning and Florida Institute for Built Environment Resilience, Univ. of Florida, Gainesville, FL 32601. Email: hhao@ufl.edu

[3]Data Scientist, Sentient Energy, Santa Clara, CA 95054. Email: chenwang@vt.edu

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Table 1. Simplistic categorization of curb uses based on time and space

Occupied space	Short-term	Long-term
Small space	Dockless bike and e-scooters	Bicycle infrastructure: bike share station, lanes, cycle tracks, multimodal paths, bike racks
Regular space	Pick-up/drop-off (MoD)	Regular parking (metered or not) electric vehicles (parking for charging) handicapped parking space
Large space	Public transport/bus stop emergency vehicle access	Freight drop-off (e.g. food truck; USPS/FedEx) commercial vehicle loading space/zone (truck)

up-to-date curb management strategies to relieve these issues (IPMI 2018). City agencies should actively seek curbside management strategies to ameliorate the increasing curbside burdens and coordinate the parking needs of different curbside user groups (APA 2019). However, the prevailing management practices for curbside spaces are not prepared to address the increasing conflicts arising from new mobility options. A few cities have launched pilot programs to test new curbside management strategies, such as prioritized curbside usages and temporary PUDO zones (Roe and Toocheck 2017; SFMTA 2020), but these programs are mostly ad hoc without systematic planning approaches developed based on empirical data. Few have acknowledged the increasingly intensive and diverse curbside uses (Butrina et al. 2020). The lack of understanding of current curbside uses across users, space, and time (e.g., transportation modes, parking time, and duration), as well as the uncertainty of future demands for different uses, make it challenging for city managers to prepare curbside management to accommodate new mobility behaviors.

Therefore, this study focuses on the increasingly intensive PUDO activities and competition for curb space uses due to the growing MoD market penetration rate. We propose a data-driven, agent-based simulation framework to help urban planners and infrastructure managers to decide the allocation of *designated PUDO zones* in curbside environments in response to the burgeoning MoD and conduct an in-depth case study of selected neighborhood blocks in the City of Gainesville, Florida, US. Specifically, we used longitudinal parking data transaction and violation data to understand existing curbside use patterns and conflicts. We leveraged POI visitation frequency data as the basis to simulate future scenarios of PUDO needs assuming that these visitations will be increasingly made through MoDs in the future. This data-driven, agent-based simulation helps to identify the needs of PUDO-designated zones (time and space) for each investigated street block across various scenarios. This work contributes to the preparation of smart and adaptive urban environments and infrastructure for emerging vehicular technologies and innovative mobility services and building cities for a shared, efficient, and low-carbon future.

Literature Review

Researchers and municipal agencies have recognized the ubiquitous challenges brought by new mobility technologies and services on curb space management. However, there is not much research examining the effectiveness of proposed strategies addressing new curb use challenges. This section reviews literature relevant to existing and emerging curb uses and management strategies.

Existing Curbside Uses and Management Strategies for Curbside Parking

Curb spaces are jointly used by various stakeholders including travelers, transportation service providers, nearby land uses, and municipal departments. Curb management that accommodates different user groups varies across surrounding land use contexts (e.g., residential or commercial), designated functions (e.g., parking, bus lanes, bike lanes, green infrastructure), type of adjacent street (minor or major arterial), and so forth. We categorized curbside uses based on the objective user groups and the occupied temporal intervals and spaces in Table 1.

Specifically, in the US, a country with more than 90% car ownership, curb management strategies have been historically dominated by self-parking management and determined by land use types, for example, the metered parking spaces in front of shops, unmetered parking in residential areas, and loading zones near supermarkets. These practices assumed that automobiles were the primary transportation mode on the street. Curbside parking was designed to meet the restrictive uses by different travelers (e.g., cyclists, motorists, drivers) and the demanded capacities to avoid spillover parking (Inan et al. 2019). However, this situation has gradually changed with high-density urban developments where the dense populations in metropolitan areas impose severe mismatches between the supply and demand of parking spaces. On the other hand, the advance of e-commerce and online platforms have promoted a variety of MoD services including app-based ridesharing/hailing (e.g., Uber and Lyft), door-to-door food/goods deliveries, private shuttles, shared mobility, and more. These services require drivers to approach curbs to pick-up/drop-off goods and passengers, which further result in increased demand for curb access (Marsden et al. 2020). Intensified curb activities are likely to arise conflicts that can spill over to streets and interfere with major road traffic. As a consequence, some cities have gradually shifted from parking-oriented to transit-oriented curb designs that prioritize transit reliability and efficiency (Roe and Toocheck 2017). Transit-oriented designs can transport more people and goods and thus increase street-side businesses. Exemplary strategies for transit-oriented curb management that have been experimented across US cities include more demand-responsive curb uses and designated PUDO zones.

Prioritizing Curb Usage Based on Demand

To prepare for the trending intensified and diversified curb uses, some municipal agencies have prioritized different curb usage needs under distinct conditions. For example, the City of Seattle defines curb spaces as "flex zone" and implemented a city-wide prioritization framework that assigns ranked curb use priorities according to streets surrounding land use. For example, curb uses that enhance access to people (e.g., bike parking, passenger loading zones, short-term parking) are prioritized in residential areas compared to access for commerce (e.g., freight and truck loading), while the inverse is true in commercial or mixed-use areas (Seattle.gov n.d.; Roe and Toocheck 2017). Similarly, in San Francisco, the local transit authority's curb management strategy includes a framework to prioritize different needs in different land use contexts for people in residential, commercial, downtown, and major attractor land use areas except for industrial land use which prioritizes access for goods (SFMTA 2020). Both frameworks discourage the use of curb spaces for vehicle storage, especially in high-density commercial areas and urban cores.

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In addition to the allocation of curb spaces for diverse uses, some cities allow change of curbside space uses and pricing with dynamic parking demands (Rosenblum et al. 2020). For example, using a curbside space as a loading zone during nighttime, as a bus stop and HOV lane during commuting time, and as a public space for parking in the evening. San Francisco implemented a demand-responsive parking meter pricing pilot from 2011 to 2013, which harnessed sensors and interconnected meters to monitor parking demands continuously and adjusted prices to achieve an average occupancy rate of 60%–80% for each block (Pierce and Shoup 2013).

Pick-Up and Drop-Off (PUDO) Zones

Due to the increasing uses of MoD services, a few cities have designated passenger PUDO spaces and maximized the curbside productivity (people served) by allowing multiple uses to share the same space (e.g., PUDO with commercial loading) or by having designations change throughout the day (e.g., by using the space for PUDO when the demand for that use is the highest) (Schaller 2019). A recent study evaluated two curbside management strategies in Seattle, WA regarding their mitigation effects on PUDO-caused slow traffic related to increasing ride-sourcing trips (Ranjbari et al. 2020). The first strategy is a change of curb allocation from paid parking to an expanded passenger load zone (PLZ). The added PLZs were open to any passenger vehicle during weekdays from 7:00–10:00 a.m. to 2:00–7:00 p.m. The second strategy further implemented the extended PLZs with a geofencing approach by Transportation Network Companies (TNCs, e.g., Uber and Lyft) which directs drivers to designated PUDO locations. Both strategies have reduced the number of PUDOs that happened in travel lanes and increased curb use compliance as well as passenger satisfaction. A recent survey on ten US metropolitan cities found that some cities have launched pilot programs for installing PUDO zones in entertainment and nightlife areas for TNC drivers to load and unload passengers, and these areas are associated with reduced collision frequencies and travel delays, and increased perceived safety by pedestrians and cyclists (Butrina et al. 2020).

Emerging Curb Uses Demands Caused by Increasing MoD

Ride-hailing and on-demand micro-transit only represent a minority share of overall trips that occur in cities nowadays but have already placed considerable pressure on existing curbside space management. The rapid rise of MoD services and future transformative mobility technologies are likely to challenge future curbside space management continuously in the following ways.

First, competitive curb space uses are likely to be fueled by the rise of shared mobility including shared bikes, e-scooters, and cars. These services have placed facilities (e.g., bikes, cars, and charging stations) at curb spaces, and people need to access curbs to use the shared vehicles. Shared mobility support transit-oriented transportation systems by offering first- and last-mile solutions (Zuo et al. 2020). The shared mobility market has exceeded $60 billion across its three largest markets including China, Europe, and the US It is predicted that shared mobility will be more commonly accompanied by self-driving taxis and shuttles with an expected annual growth rate in market value over 20% through 2030 (Mckinsey Center for Future Mobility n.d.). Second, the trend of increased MoD services and PUDO activities will be reinforced by the emerging concept of SAVs, which can reduce citizens' reliance on private vehicles and free up abundant parking spaces in urban areas (Davidson et al. 2016). Several ride service companies have expressed their intentions to offer MoD services with AVs when the technologies are ready (ITF 2018). A working group of international non-governmental organizations (NGOs) even contended that AVs in dense urban areas should only be operated in shared fleets to provide affordable and equitable access to all citizens (Chase 2017). Some recent studies that investigate SAV operations in simulated scenarios suggested that parking SAVs at locations where they finished before trips (i.e., curbside spaces) can reduce energy consumption and shorten passengers' waiting time compared to storing them in garages (Kondor et al. 2020; Winter et al. 2020). Additionally, considering that these transformational technologies and associated infrastructures have emerged over the last decade, municipal agencies should plan for more diverse and heterogeneous traveling modes and curb usage brought by future innovations.

The projected rapid MoD increments in the near future also attract researchers to investigate its various associated impacts. For example, studies have used agent-based modeling (ABM) to simulate future parking demands and showed that the adoption of SAV and MoD can remove more than 80% of the parking spaces in urban areas (Zhang and Wang 2020; Kondor et al. 2018; Zhang et al. 2015), but the associated MoD network rebalancing and AV relocation may generate significant empty vehicle miles traveled (VMT) and cause traffic congestion (Kondor et al. 2018; Oh et al. 2020). Other simulation-based studies determined the beneficial impacts of the increased adoption of MoD and SAV on the environment, energy use, safety, and transportation efficiency (Wadud et al. 2016; Fagnant and Kockelman 2014; Greenblatt and Shaheen 2015). However, very few have studied the management of the built environment to accommodate emerging transportation technologies despite a limited number of studies intended to predict the needs of charging infrastructure for electric AVs based on real-world traffic data, energy modeling, and vehicle battery life using ABM-based models (Bauer et al. 2018; Zhao et al. 2020). Other researchers used microscopic simulations and simulated traffic to examine the design of curbside parking bays and curbside lane allocations (Wang et al. 2018; Ye et al. 2020). These studies did not investigate detailed curbside management strategies such as designating the number of PUDO zones for specific urban neighborhoods.

Cities need to provide adequate curb spaces and efficiently manage the growing competition between different curb usages. Failure to do so may exacerbate conflicts among different curb users, negatively impact curbside businesses, and jeopardize roadway safety. This literature review has shown that some cities have started to address the challenges brought by emerging mobility services and launched pilot programs to test new curbside management strategies, but these efforts were evaluated as "generally ad hoc and based on professional judgment" and "more of an art than a science" (Butrina et al. 2020, pp. 5). Additionally, existing transportation modeling literature focused on curb management practices and policies are dominated by parking concerns without considering the conflicts that arise from increased PUDO activities. Thus, we propose a data-driven, agent-based simulation framework to help urban planners and infrastructure managers decide the allocation of designated PUDO zones in curbside environments in response to the burgeoning MoD in the near future.

Case and Data Description

Case Description

The City of Gainesville, where the University of Florida (UF) s located, is developing rapidly from a college town to a polycentric metropolitan area with nearly 130,000 residents. The community has large fractions of pedestrian traffic with increasing micro-mobility (Bosa 2019; University of Florida 2018; City of Gainesville n.d.). Moreover, the line between pedestrians' wheeled mobility and powered mobility is becoming blurred. The city has set strategic goals of improving equitable and convenient access, supporting electric vehicles (EVs) and renewable energy, and developing effective on-demand services for all citizens (City of Gainesville 2020), which has been challenged by the (1) escalating local ownership of plug-in EVs with limited public charging stations for residential blocks in the urban core; and (2) the booming PUDOs encouraged by e-commerce and MoDs. According to the latest UF transportation survey, traffic congestion and poor last-mile connections across campus are mainly attributed to limited curb parking spaces, unprogressive curb management strategies for coordinating emerging micro-mobility, and PUDOs with restrictive parking spaces (University of Florida 2018).

We collected spatial data of all curbside parking spaces from the City of Gainesville-Transportation office and POI data from the SafeGraph platform. The curbside parking spaces were mostly located to the north and east of the campus and the downtown, which is surrounded by shops, restaurants, hotels, governmental buildings, and single/multiple residences (Fig. 1). Most curbside parking spaces have specified restrictions on vehicle types (e.g., scooter, motorcycle, freights, and vehicles), parking duration (e.g., 30 min or 2 h), and regulations (e.g., meter, decal, reservation, and time limit), with very few denoted as free usage. According to the parking transaction and citation data obtained from the city, the eastern Innovative Zone and northern campus are notably characterized by traffic congestion, parking space shortage, and violated road and curb usages due to the high and varied traffic flow associated with students and commercial activities.

Parking Data Description

We used one-year parking-relevant datasets from March 2019 to February 2020 (before the COVID-19 pandemic) provided by the City of Gainesville to investigate the urban core's curbside parking occupancy and conflict patterns. The datasets include (1) curbside parking transaction records (collected from meters and pay-by-app records); and (2) on-street parking violation citations. The full-year data enables the examination of spatial and temporal changes of curb space demands and conflicts.

Parking Transaction Records

During the study period, there were 95,607 parking transaction records for 42 curbside parking spaces in the urban core of Gainesville. For each street, we referred to Google Street Views to determine the parking capacity of distinct curb spaces. We defined curbside parking capacity as the maximum number of parked vehicles permitted in that curbside parking space, and the parking occupancy rate was calculated as the ratio of the number of actual parked vehicles and the parking capacity. We computed the occupancy rate for each operating hour for the 42 streets and divided the streets into three groups based on their locations, i.e., Downtown, Campus North, and Innovative Zone. Fig. 2 shows the average parking occupancy over a week for streets in the three different zones. The figure shows great variances of the occupancy rates of curbside parking spaces in different zones, where streets to the north of the campus can reach around 60% occupancy rate during peak hours (10:00 a.m. to 4:00 p.m.) on average while the curbside parking spaces on downtown streets are relatively under-used. Paid parking is mostly available from 7:00 a.m. to 6:00 p.m. over weekdays with a few meters charging fees till 7:00 p.m. To demonstrate the general parking availability across

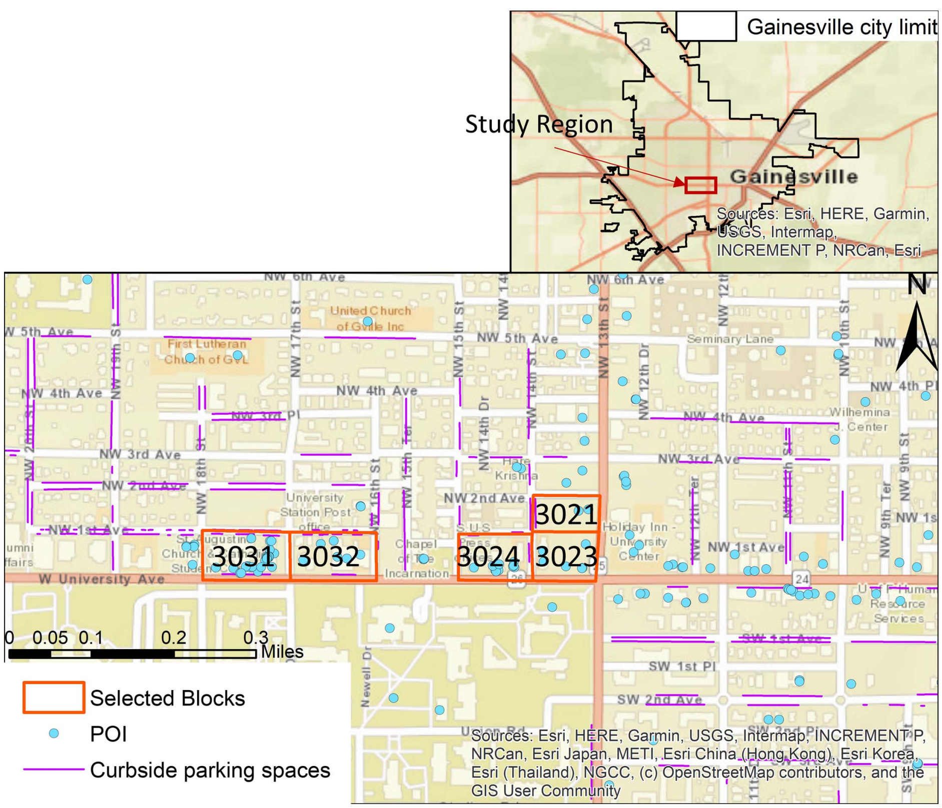

Fig. 1. Map of the studied area. [Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community.]

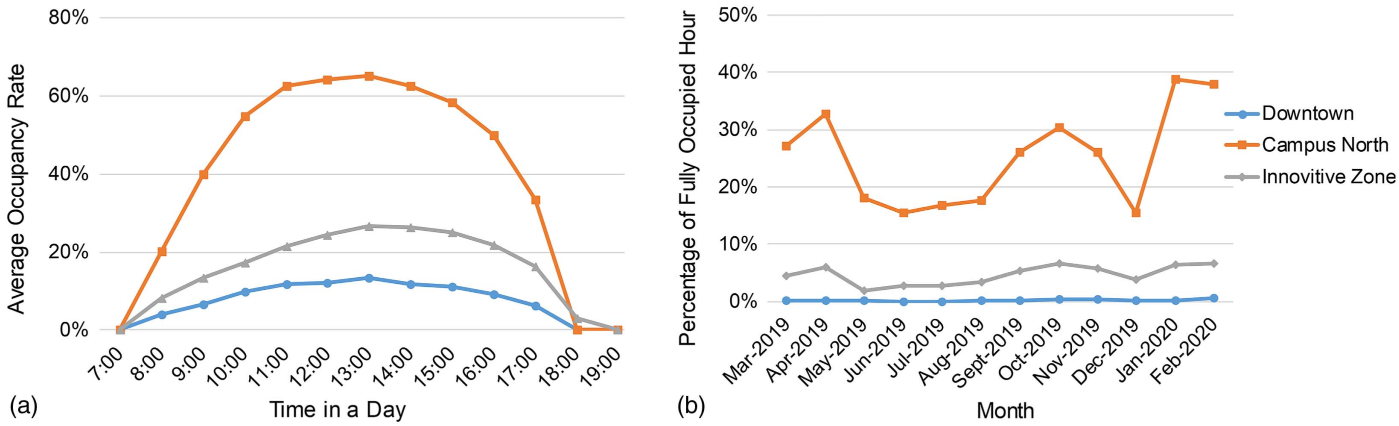

Fig. 2. Temporal patterns of parking occupancy for urban core streets: (a) hourly average parking occupancy; and (b) monthly percentages of fully occupied.

curbside spaces over the year, we also calculated the percentage of hours that the curbside parking spaces are fully occupied (i.e., with an occupancy ratio of 100%) in different months based on the total metered hours [Fig. 2(b)]. It shows that the parking needs from May to August and December are lower than other months because students have left campus for holiday breaks.

Parking Violation Tickets/Citation Data

There were 2,699 parking violation citations over the data collection period of 27 types, including parking in wrong places (e.g., parked on sidewalk/bike lane), overtime parking (e.g., expired meter), sign violation, and parking in an improper manner (e.g., blocking/interfering traffic). We have also divided these violation citations into three types suggesting conflicting space uses (e.g., blocking/interfering with traffic), conflicting parking time (e.g., overtime/feeding meter), and improper parking manner (e.g., double parking). Most (64%) of these parking citations reflect the conflicts within and among different road users such as pedestrians, cyclists, and drivers [Fig. 3(c)]. These citations were mainly issued between 8:00–10:00 a.m. and 2:00–4:00 p.m. [Fig. 3(b)], and all three citation categories peaked at 9:00 a.m. A few citations denoted as space conflict (e.g., Parked on sidewalk/bike lane) were also found in the early morning hours. The number of issued citations also fluctuates with months as fewer citations were discovered in the summer months from May to August [Fig. 3(a)]. Parking citations that denote conflicting curbside uses include parked on sidewalk/bike lane, parked

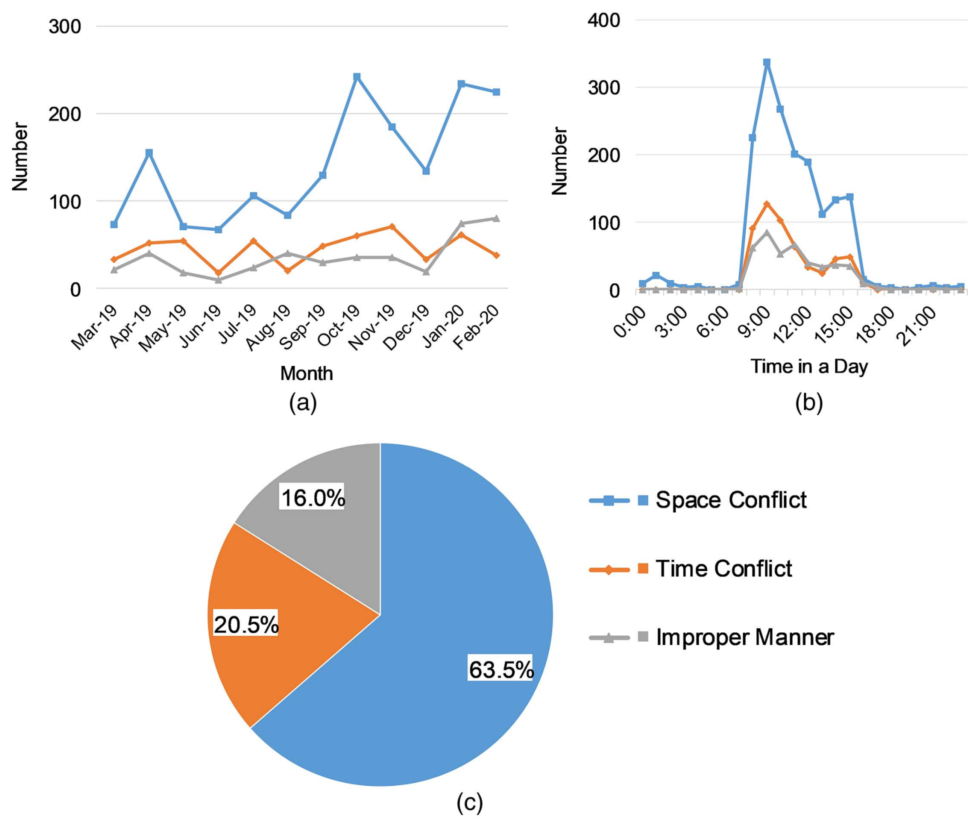

Fig. 3. Number and percentage of different categories of parking citations.

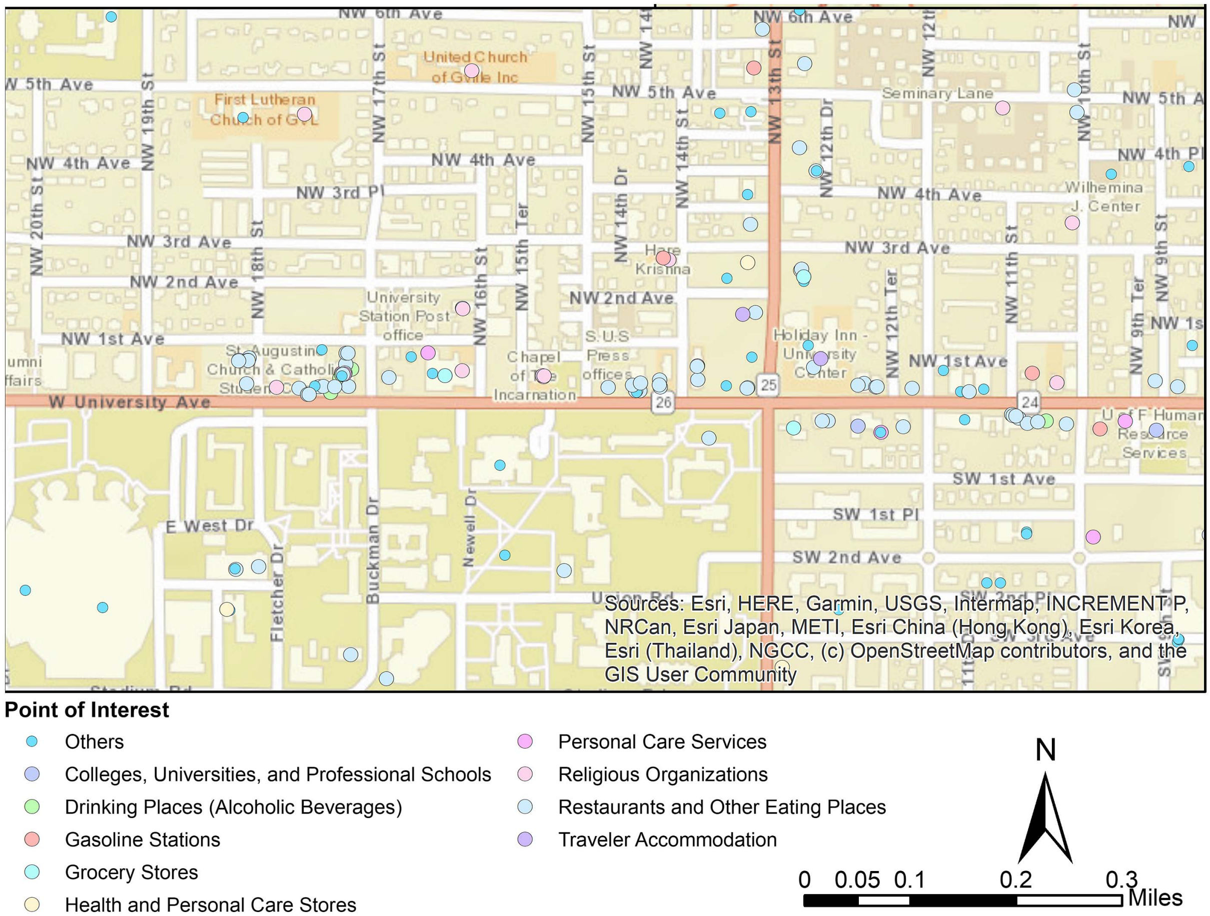

Fig. 4. Spatial distribution of POIs in the urban core of the City of Gainesville, FL. [Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community.]

w/in 1.5 m (5 ft) of drive, and blocking/interfere w/traffic, among others.

Point of Interest (POI) and Visitation Frequency

The POI data collected from the SafeGraph platform include POI location and categories. In addition to this location information, SafeGraph also collects traffic patterns that tell people's visiting frequencies, durations, and origins (deducted in census blocks) of each POI. There are a total of 706 POIs in the study region, many of which are located along University Avenue and in downtown Gainesville (Fig. 4).

Street Blocks Selection

We mapped the average curbside parking occupancy and POI densities in Fig. 1 using a bivariate map. Based on the mapped block level parking demand, we selected five blocks to focus on PUDO zone allocations, including Block #3021, #3023, #3024, #3031, and #3032. Inside the five blocks, there are 50 POIs of 17 types (Fig. 5). Curbside parking spaces are allocated around these street blocks. We show the average hourly visitation frequencies in the five selected blocks in Fig. 6. It can be found that most people visited these blocks for restaurants, amusement, and traveler accommodations. Blocks #3023, #3024, and #3032 were mostly visited during the daytime and evening while Blocks #3021 and #3031 were visited more frequently after 7:00 p.m.

Methodology

The objective of this research is to propose an agent-based simulation (ABS) framework to decide the allocation of designated PUDO zones in curbside parking spaces at a street block level. ABS is used in this research considering its advantages in modeling collective unpredefined behaviors that emerge from individual agents heterogeneously (Du and El-Gafy 2015). Each *agent* represents a person who drives or uses a vehicle to visit a POI inside a street block and also uses the curbside for (1) self-parking (private vehicles), (2) drop-off (MoD), or (3) pick-up (MoD). The agents' curbside usage behavior, characterized by their destination (i.e., a POI within a specific street block), arrival time, and stay time, are simulated based on the distributions generated from real-world longitudinal data.

We constructed three distinct simulation scenarios with critical thresholds of MoD market penetration at 10%, 30%, and 50%. Note that we did not emphasize the specific years by when the MoD market penetration may achieve the certain percentage thresholds as none of the existing studies and reports have provided detailed estimations of MoD market penetration for specific cities. We mainly used the listed percentages to provide thresholds for simulating curb use demand by PUDO activities in the near future. Based on the self-parking behavior patterns and the estimated MoD curb usage patterns derived from real-world big data, we ran agent-based simulations across the three scenarios to examine the curb use demand incurred by PUDO. Specifically,

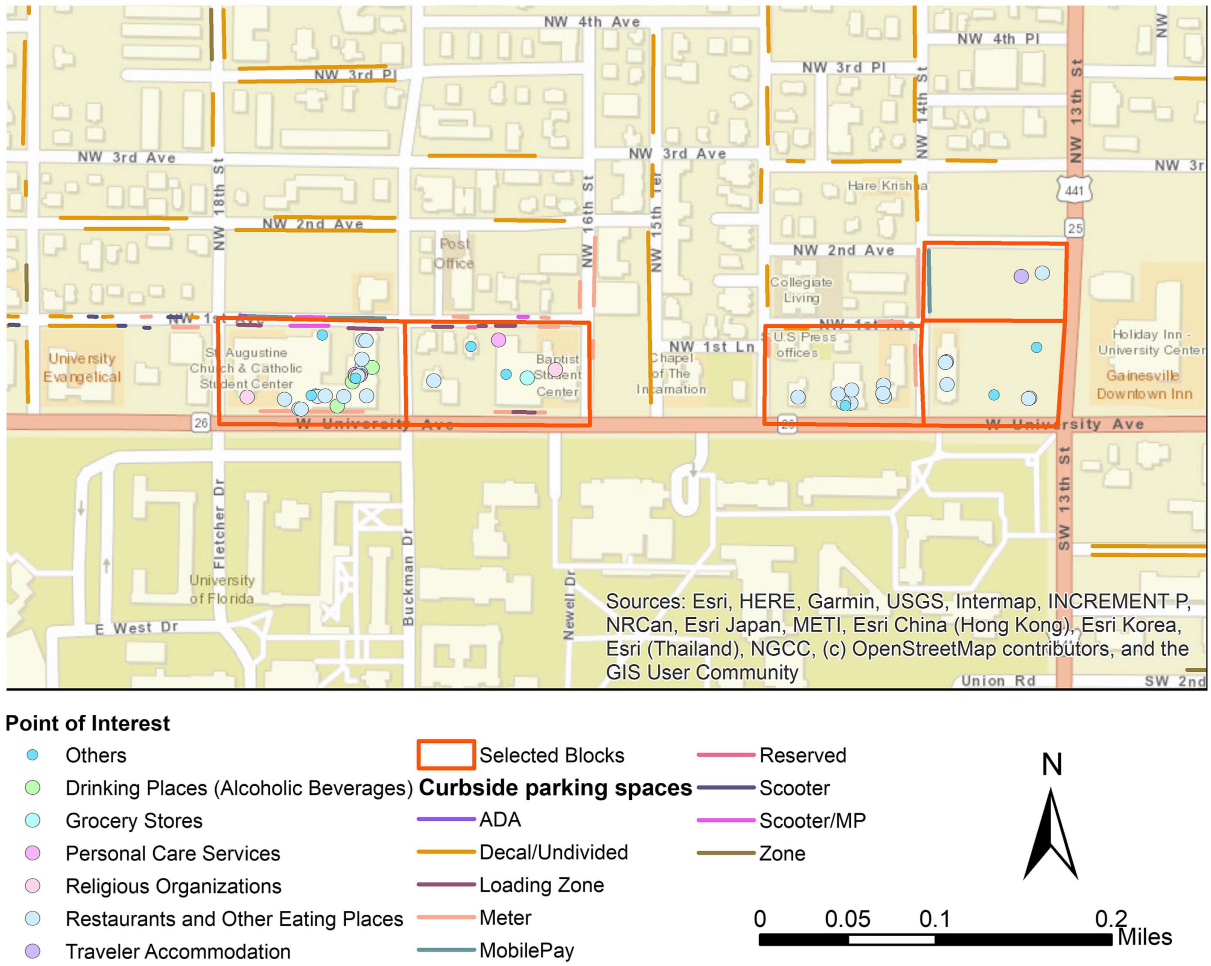

Fig. 5. POIs and curbside parking spaces within and around the five selected street blocks. [Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community.]

based on the availability of real-world datasets and our empirical investigations of existing curb space usage patterns in the urban core of Gainesville in the section "Case and Data Description," we defined our study time of a day from 8:00 a.m. to 6:00 p.m. including ten consecutive daytime hours. To achieve a fine temporal scale of designating PUDO zones, weekdays from Monday to Friday are differentiated when we generated distributions based on current data, and weekends data was excluded due to much lower curb use demands in the studied city.

Major Assumptions and Algorithm for the Data-Driven ABM

To simulate future curb uses by self-parking and PUDO based on distributions and patterns retrieved from existing datasets, we make the following assumptions:

Assumption #1: An MoD vehicle has priority to use an empty curbside spot around a street block for PU and DO activities; if the curbside space around a street block is fully occupied when the vehicle arrives, the vehicle will compete with the curbside usage with the parked vehicles and cause a *competing use event*, such as parking on travel lanes or double parking.

Assumption #2: Distributions of curbside self-parking vehicles' number over distinct time units retrieved from the eight-month dataset can represent self-parking patterns in simulated future scenarios. This assumption is based on the anticipation that people who own vehicles will be the last to use MoD, so at the early stages of AV deployment, they will still use their private vehicles for self-parking instead of using MoD.

Assumption #3: Each curbside's parking time limits for self-parking remain the same as their current regulations across the three simulation scenarios. Under this assumption, based on the arrival time, we use the corresponding distributions of stay time retrieved from the parking occupancy data to represent the stay time of all visitors regardless of using MoD or private vehicles across future scenarios.

Assumption #4: Pricing is standard hourly prices and is the same across curbside parking spaces in the studied area. In this way, self-parking patterns retrieved from the existing dataset can still be useful for simulating future self-parking patterns even if the standard hourly price for all curbside space slightly changes. As long as the price is still the same across the studied curb spaces, people will not change their preferred parking location due to the differing costs of self-parking.

Assumption #5: There are no changes in land use of the studied urban core areas located near the POIs/blocks. Based on the City-University's strategic plan, the land use of the studied area will not change over the next few decades; the specific POIs (e.g., restaurants) may change but will generally fall into the existing categories due to the stable needs from people who work and study in the nearby university campus.

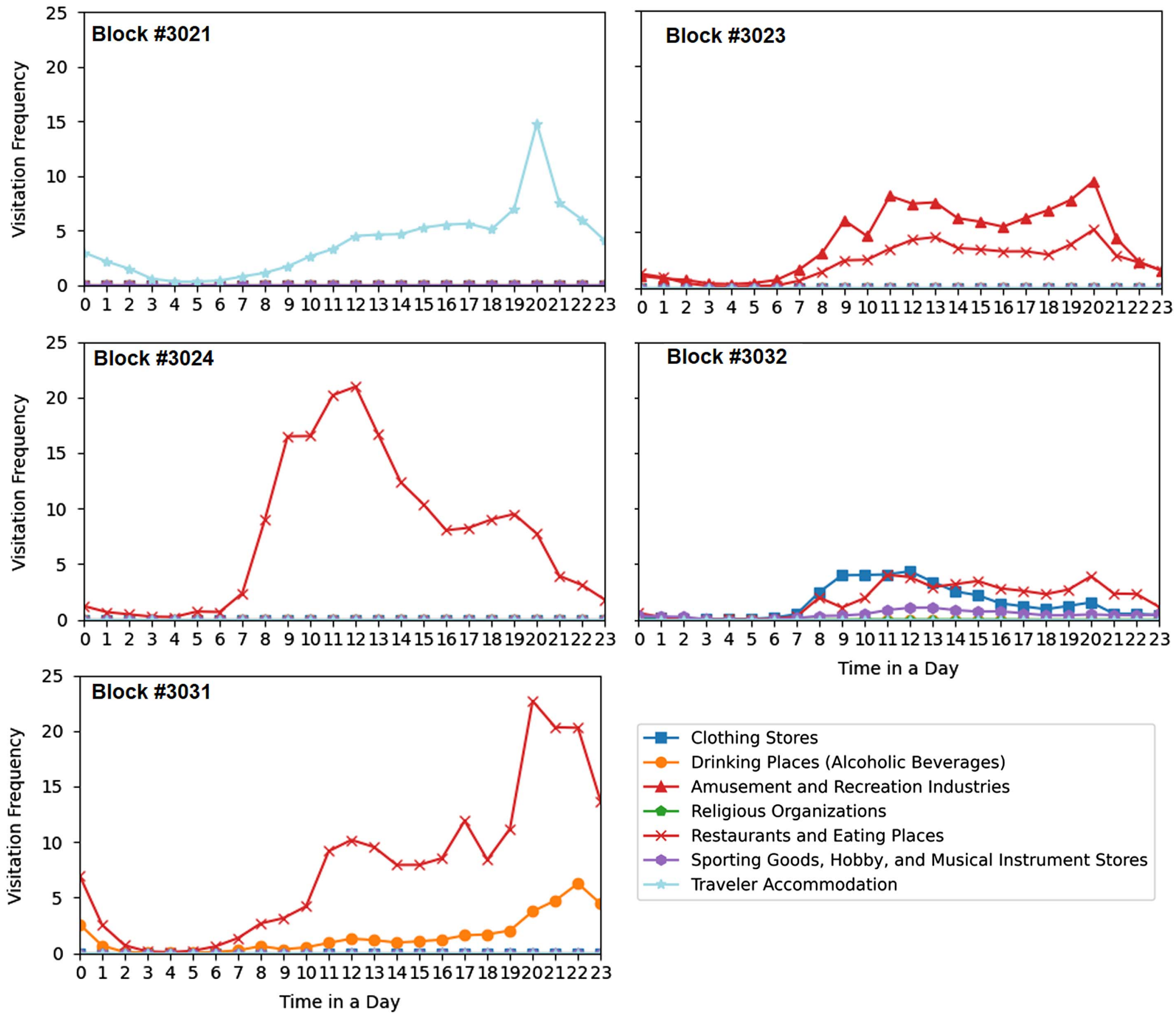

Fig. 6. Hourly POI visitation frequencies over an average day across the five selected blocks.

Assumption #6: No ridesharing (one vehicle for one passenger) when visiting the POIs in urban cores due to the diversity of origin/destination locations. Thus, visitation frequency retrieved from the existing dataset for collective individuals can serve as a basis to simulate future visitation patterns.

Assumption #7: Passengers who use MoD to visit the block (drop-offs, DO) also use MoD to leave (pick-ups, PU), so an agent who uses DO to arrive (curb use) at a street block is expected to use PU to leave (curb use) after a stay time.

The basic *idea* is that, *over a distinct time unit (i.e., an hour), if the overall uses for self-parking, drop-offs, and pick-ups exceed the curb space capacity, there are competing curb use events (i.e., competing events) and the exceeded number of uses is regarded as the number of events of the competing curb space uses*. The more competing use events that occur over a certain time window on a weekday for a block, the higher need for designated PUDO(s) for the block (Assumption #1). The algorithm for simulating curbside PUDO activities and competing events is shown in Fig. 7. The outcomes intend to inform curb management decision-making regarding: (1) at what MoD market penetration rate a street block may need designated PUDO zones? (2) which days during the week and time during the day should curbside parking zones be designated as PUDO zones? and how many? Detailed methods at the fine spatial and temporal scale are demonstrated in the following subsections.

Main Elements of Agent-Based Simulation

Retrieving Curbside Self-Parking Occupancy Patterns

For our selected five street blocks, all curbside parking spaces are public and have meters, so the parking occupancy data retrieved from the meter (i.e., transaction data) can represent the overall usage of curbside spaces at the street blocks. We used the parking transaction data over eight months to retrieve the self-parking patterns, which will be used to simulate future self-parking uses of curbside spaces (Assumptions #2, #3, #4). Data from June, July, August, and December are excluded as most students left the college city during the summer and winter holidays [Fig. 2(b)]. Specifically, for each hour between 8:00 a.m. and 5:00 p.m. on a weekday, the historical parking occupancy records from the same time unit at the concerned block were used to retrieve the pattern.

We fitted the data using the Matlab function "fitmethis" (de Castro 2021), which tested the data across five discrete distributions including Binomial, Negative Binomial, Discrete Uniform, Geometric, and Poisson distribution, and used log-likelihood and Akaike Information Criterion (AIC) as evaluation metrics to find the best fit. When the five distributions failed to approximate the actual parking behaviors, a Normal distribution was used as a backup fitting option. During certain time units, some curbs were not used, which incurred '0' occupancies in the records; and when

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Algorithm 1 Curbside PUDO activities and competing events simulation

Input: Future scenarios set, $\mathbb{Y}$; Simulation times, N; Concerned block set, $\mathbb{B}$; Concerned block capacity set, $\mathbb{C}$; Concerned weekday set, $\mathbb{W}$; Concerned business hour set, $\mathbb{H}$; Self-parking number distribution set $\mathbb{D}_{park}$; Visit frequency distribution set $\mathbb{D}_{visit}$; Stay time distribution set $\mathbb{D}_{stay}$

Output: Simulated congestion record , $\mathbb{R}_{cgstn}$

Loop through interested future scenarios :

for i^{th} future year $\in \mathbb{Y}$ **do**
  find corresponding PUDO ratio, r_i
  Simulate N times :
  for $iter = 1 : N$ **do**
    for j^{th} weekday $\in \mathbb{W}$ **do**
      for k^{th} business hour $\in \mathbb{H}$ **do**
        for l^{th} block $\in \mathbb{B}$ **do**
          find corresponding self-parking number distribution $\mathbb{D}_{park}(j, k, l)$
          generate self-parking number in current hour at current block, $p_{j,k,l}$
          find corresponding visit frequency distribution $\mathbb{D}_{visit}(j, k, l)$
          generate visit frequency in current hour at current block, $v_{j,k,l}$
          calculate DO number in current hour at current block, $v^{(DO)}_{j,k,l} = ceil(v_{j,k,l} * r_i)$
          calculate current curb occupancy, $O_{j,k,l} = p_{j,k,l} + v^{(DO)}_{j,k,l}$
          if there exist DO events at this moment, or $v^{(DO)}_{j,k,l} > 0$ **then**
            find corresponding stay time distribution $\mathbb{D}_{stay}(j, k, l)$
            for each DO event **do**
              generate stay time for the current DO curb use, t
              round t to number of hours, t_h
              add future PU curb use, $v^{(PU)}_{(j+t_h),k,l} = v^{(PU)}_{(j+t_h),k,l} + 1$
            end for
          end if
          calculate current final curb uses, $O_{j,k,l} = O_{j,k,l} + v^{(PU)}_{j,k,l}$
          find curb capacity of current block, $\mathbb{C}(l)$
          calculate curb competing uses events in current hour at current block, $cgstn_{j,k,l} = max[(\mathbb{C}(l) - O_{j,k,l}), 0]$
          record competing curb uses result $cgstn_{j,k,l}$ in $\mathbb{R}_{cgstn}$
        end for
      end for
    end for
  end for
end for
return $\mathbb{R}_{cgstn}$

Fig. 7. Algorithm for the data-driven agent-based simulation.

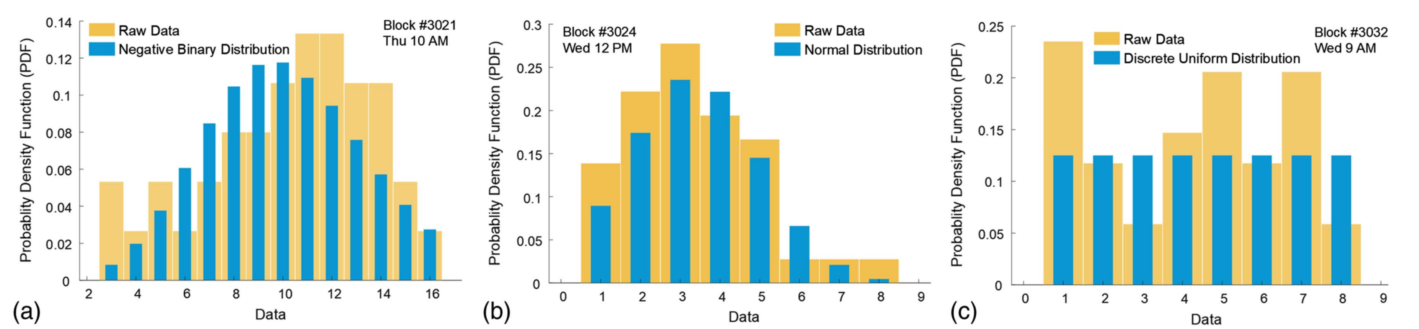

Fig. 8. Histograms of raw parking occupancy data and the corresponding fitted distributions for the three studied blocks in specific time units.

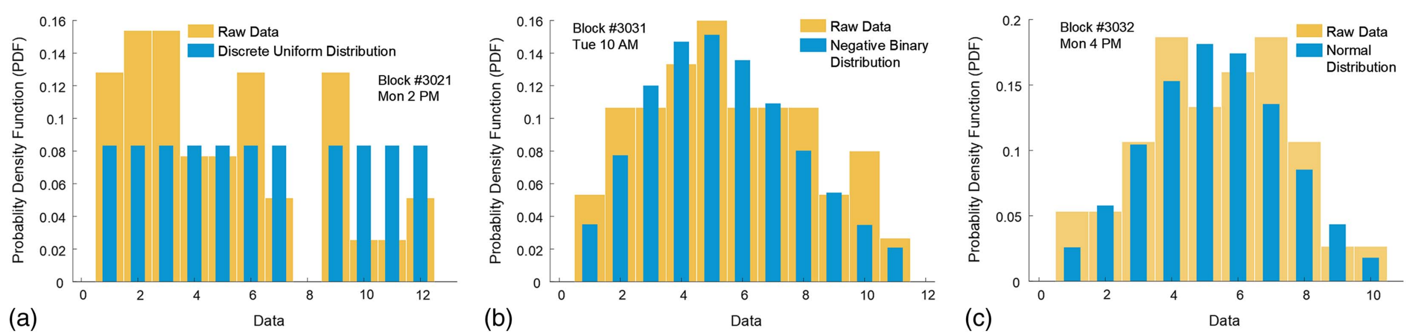

Fig. 9. Histograms of raw visitation frequency data and the corresponding fitted distributions for the three studied blocks in specific time units.

fitting the Negative binomial distribution to the data, there was a large probability of invalid parameters. Therefore, without loss of distribution information, we added '1' to each parking record to avoid invalidity, then subtracted '1' from the randomly generated numbers of self-parking in the simulation. Finally, we plotted the frequency distributions for curbside occupancies during a specific time unit over a distinct day and obtained 50 distinct distributions to characterize the occupancy patterns. All plots are included in the Supplemental Materials. Fig. 8 demonstrates three examples of curbside occupancy patterns by self-parking for specific blocks during different time units of the studied daytime.

Predicting PUDO Uses Based on POI Visitation Frequency and Stay Time Patterns

Predicting Drop-Off activities' demand per block in distinct time units. We refer to drop-off activities with the obtained POI visitations as they capture the fine-grained spatio-temporal dynamics regarding residents' activities and the demands for curbside access. Though residents may approach the curbsides with different transportation tools, it is predicted that these transportation tools will be gradually overtaken by MoD services with SAVs to pick-up and drop-off passengers at curbsides in the future.

Because many POIs inside our studied street blocks in the urban core areas have private parking spaces and some people may use the private parking spaces inside the block, we cannot use the aggregated visitation frequency to all POIs in each block to infer the curbside parking demands in the public space. However, we assume that the self-parking use pattern (i.e., distributions of visiting frequency) of curbside space is maintained the same over time when MoD market penetration rate increases to 50% considering MoD services are mainly used by passengers of non-private vehicles at the beginning stages (ITF 2018), and the collected POI visitation data mainly reflect travel and access modalities including parking in private parking space, walking, using micro-mobility vehicles (e-scooter and bicycles) or taking buses. We justify this assumption based on how the POI visitation data were retrieved by SafeGraph from the raw mobile device GPS data. Based on SafeGraph's technical guide for detecting a visit to a POI, the algorithm "finds the closest POI centroid and calls it a visit to that POI if the distance is below some threshold: any GIS Ping inside a building polygon is a visit" (SafeGraph 2020). Considering the order of magnitude difference between POI visitation data and parking meter records, the impact of including certain noise from curbside parking can be omitted.

We examined and approximated the distribution of visitation frequency for each block by aggregating the visit numbers to POIs in each block per time unit over the eight months. Similar to the process of fitting self-parking patterns in the section "Main Elements of Agent-Based Simulation," we obtained 50 distributions of block visits for all time units and each studied block. All plots are included in the Supplemental Materials. Fig. 9 demonstrates three examples of street block visitation frequency data for specific blocks during different time units of the studied daytime.

Retrieving Stay Time Patterns from Parking Occupancy Data. For simulating the *stay time* of arrived visitors who are dropped off during each time unit, we adopted the fitted distribution of block visitors' stay time based on the current parking occupancy data. The distribution of stay time is also approximated with discrete distribution fitting. It is worth noting that the stay time records exist only when there are corresponding parking events, so there is no '0' minute stay time. The discrete distribution based on the original time unit (i.e., minutes) can satisfy the simulation requirements for hour-based distribution approximation, and in the simulation, randomly generated stay time data are rounded into hourly units to fit the model. As we assume that passengers who use MoD to visit the block (drop-offs, DO) also use MoD to leave (pick-ups, PU), the curb uses of pick-up activities (PU) over a time unit are determined by previous DO activities and stay time (Assumption #7). Fig. 10 demonstrates three examples of histograms of raw stay time data and the corresponding fitted distribution for arrival in distinct time units for a specific block.

Agent-Based Simulation Results

For each block, the simulations were run in Matlab 10,000 times for each time unit across three scenarios where MoD market penetration rates are different. We show the 10,000 times simulation outcomes over five weekdays for the three experimental scenarios in Figs. 11 and S2. The values on the heatmaps are the average number of competing use events that occurs at curbs outside the investigated blocks (Fig. 11), and the probabilities of competing use event occurrence (Fig. S2) in each hourly interval when there was no designated PUDO zone. Both figures demonstrate temporal patterns of the competing uses of curbside spaces between self-parking and PUDOs. We found that more competing use events would happen between 9:00 a.m. and 3:00 p.m. (in the middle of the day) compared to the early morning (8:00 a.m. to 9:00 a.m.) and late afternoon (3:00 p.m. to 5:00 p.m.). Blocks #3023 and #3024 show significantly higher demands for designated PUDO zones given the high number of competing use events and probabilities of the occurrence of competing use events over the five weekdays, followed by Block #3032. Both Block #3023 and #3024 face the major road, i.e., the University Avenue, which has 6 and 10 POIs for eating services and amusements and attracts many daytime visits from students and faculty (Fig. 6).

When comparing different simulated MoD market penetration ratios, results show that though under a low market penetration ratio

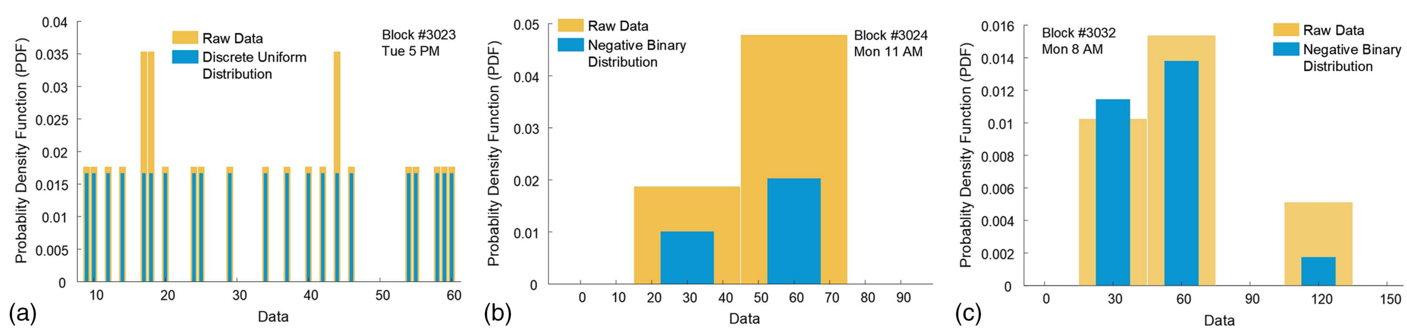

Fig. 10. Histograms of raw stay time data and the corresponding fitted distributions for arrivals in distinct time units for three specific blocks.

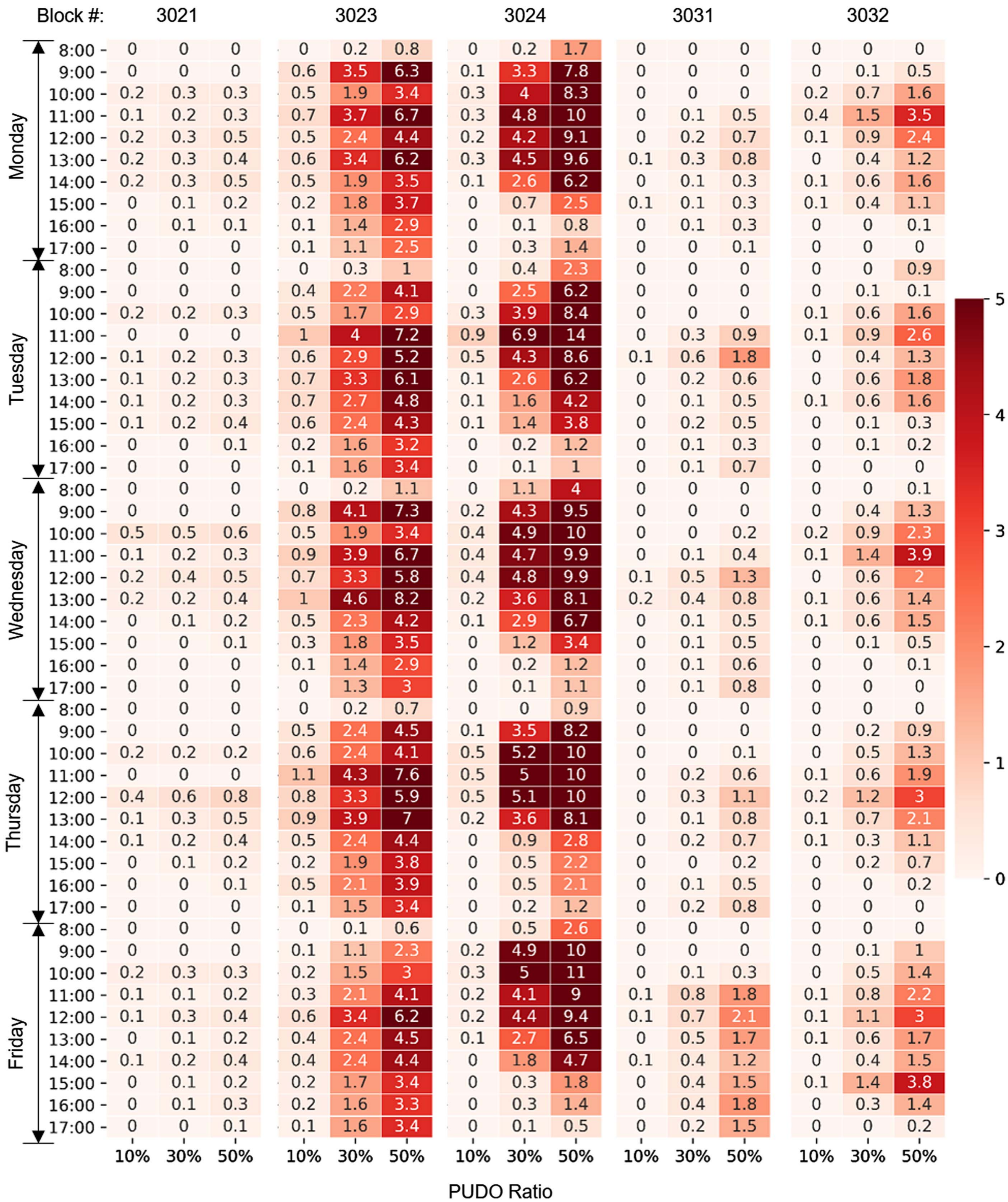

Fig. 11. Average number of curbside competing use events with no PUDO parking space.

of 10%, there is still a 5%–15% likelihood of competing use event occurrence for the three least congested blocks (i.e., #3021, #3031, and #3032) and 35%–50% for the two most popular blocks (Block #3023 and #3024) during the peak hour (Fig. S2), which suggests the potential demands of time limit designated PUDO spaces for these blocks during peak hours. The curbside parking spaces become even more stressful when the market penetration of MoD increases to 30% and 50%. Alongside the significant increments observed in the number of competing use events, the probabilities of event occurrence also increase to 70%–95% during peak hours for the two congested blocks (i.e., #3023 and #3024) (Fig. S2), which suggests frequent competitive curbside uses between PUDO drivers and self-parking drivers if the city continues with its existing curbside parking space design. Non-peak hours are also associated with high probabilities of competing use events over the five weekdays. The most severe competing use scenario, i.e., Block #3024 with a 50% MoD on average, has 6 to 14 competing use events happening during each hour over weekdays. In this case, the city may consider allocating designated PUDO spaces at curbs near Blocks #3023 and #3024 on weekdays.

We then examined the effectiveness of designating PUDO zones for different blocks. Fig. 12 shows the simulation results that

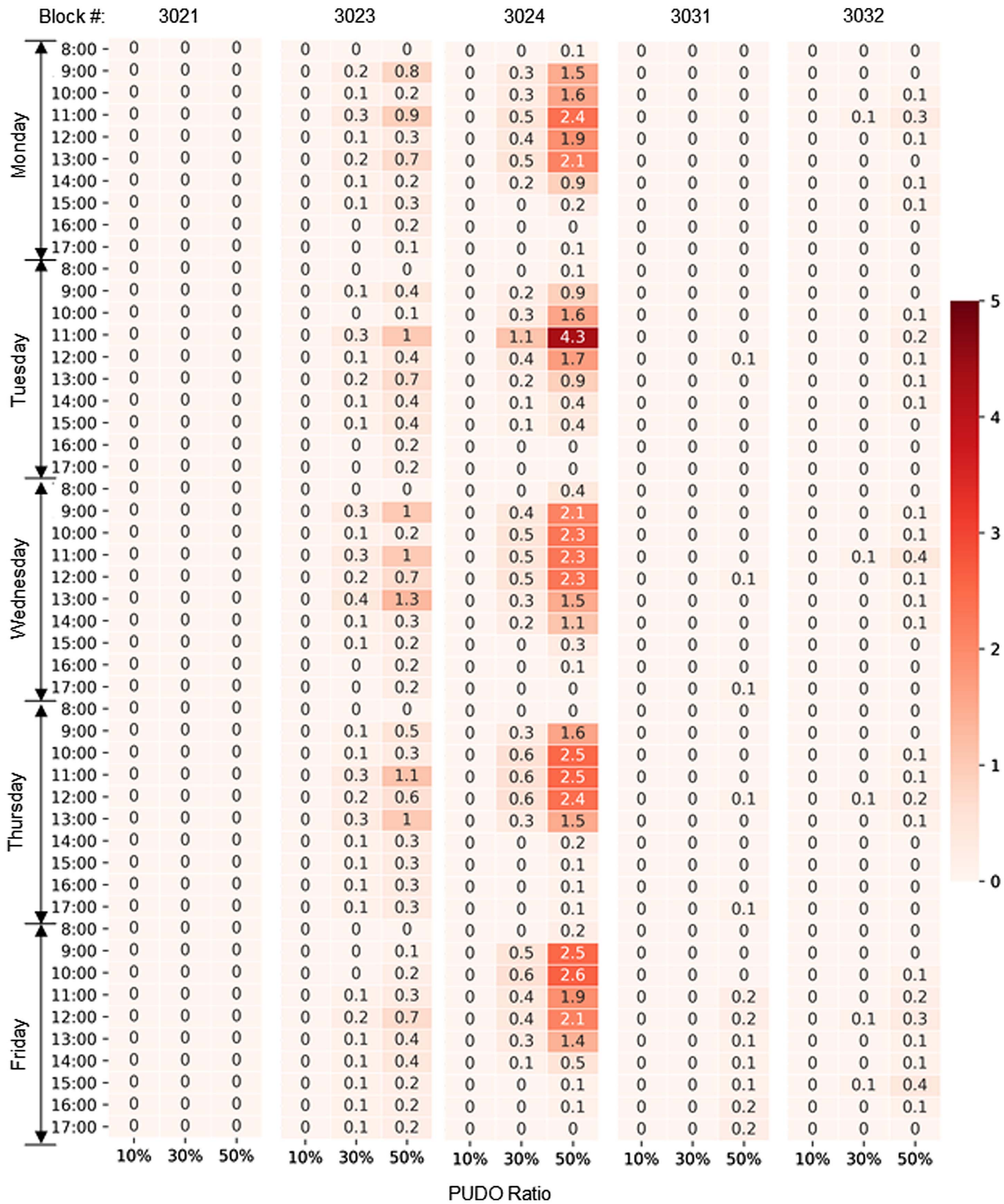

Fig. 12. Average number of curbside competing use events with one designated PUDO zone and 3-min dwell time.

assume each block has one designated PUDO zone transformed from a conventional parking space. We set the dwell time for vehicles' PUDO operations to be three minutes based on the existing empirical findings (Goodchild et al. 2019), which shows three-minute dwell time can satisfy 85% of TNC passenger PUDO operations occurring curbside (Goodchild et al. 2019). Other studies also suggested 20 seconds (Zhang et al. 2020) and 2.5 min (Young and Henao 2020) for PUDO dwell time. ABS simulation results show that a single designated PUDO zone can largely reduce the average number and occurrence probabilities of the competing use events. A temporal PUDO zone designated during peak hours (i.e., 9:00 a.m. to 3:00 p.m.) is sufficient for Block #3021 across the three scenarios with different PUDO market penetration rates, as the low average competing use event numbers of 0.1 and 0.2 suggested in Fig. 12. The inclusion of a single PUDO parking space also satisfies the other four blocks' uses under a low market penetration ratio of 10% (Fig. 12).

We further conducted sensitivity analyses to show how the effectiveness of PUDO designation can be influenced by the number of transformed PUDO zones and the length of PUDO operation dwell time. We tested different numbers (i.e., 0, 1, and 2) and dwell time (i.e., 1, 2, and 5 min). These results are presented in Figs. S1–S10. Specifically, for the most challenging scenario (i.e., Block #3024 with a 50% MoD), the transformation of one PUDO zone can reduce the average competing use event number by 5–6 (or 40%–50%) during peak hours (Fig. 12), while the two PUDO zones can reduce the number by 8–10 (or 70%–80%) (Fig. S7). In a scenario when the MoD platforms and clients are well-coordinated and the average dwell time is limited within one minute, a single designated PUDO zone can relieve the curbside stress for Blocks #3021, #3031, and

#3032 well under all hypothesized market penetration rates (Fig. S9). Compared to two PUDO parking spaces with an average dwell time of three minutes (Figs. S7 and S8), the designation of one PUDO parking space can achieve equal or even better performance regarding mitigating competing curbside uses when the average dwell time is within one minute (Figs. S9 and S10). This finding suggests that city managers and MoD service providers may encourage technical or planning strategies, such as geofencing and repurposing curbside spaces, to reduce the PUDO dwell time for more effective curbside management.

Discussion

The digital records from parking meters and smart mobile phone devices enable longitudinal research on generalizable patterns of human-environment interactions. We constructed a digital twin of curbside space uses based on the collected parking meter transaction data and visitation frequencies from parking meters and individuals' mobile devices. Derived from fine-grained datasets, we propose a data-driven agent-based modeling approach for city managers and infrastructure planners to prepare their curbside management strategies in response to the increasing market penetration of MoD. The study contributes to the knowledge body of infrastructure and asset management by providing a data-driven management framework to relieve the increased competing uses on limited curb spaces. The proposed curb management framework intends to address the increasing short-term parking needs of PUDO, simulates future curb uses by self-parking vehicles and PUDO activities across scenarios, thus suggesting detailed management strategies for designated PUDO zones (time and size) in public curbside parking spaces at street block levels. We conducted a detailed case study on five selected street blocks in the urban cores of the City of Gainesville, FL using longitudinal parking transaction and violation data, place visitation data, and geospatial parking assets data. Simulation results show that even under a low PUDO market penetration rate of 10%, the designation of temporal time limit curbside PUDO zones in peak hours should be considered for all five studied blocks to mitigate the occurrence of competing usages. With a higher penetration rate of 30% or 50%, the City should consider permanent PUDO zones for the two most visited blocks (i.e., Block #3023 and #3024) while other blocks also need expanded service time of temporal PUDO zones. The results also illustrate the effectiveness of PUDO designation on mitigating competitive curbside conflicts. The curbside competing use events can be reduced by 40%–50% for the most challenging curbside use scenario with one designated PUDO zone, which increases to 70%–80% with two PUDO zones. The sensitivity analyses suggest that the curbside regulations should be implemented for both the spaces (e.g., the number and location of designated PUDO zones) and the uses (e.g., PUDO dwell time) to achieve a more effective curbside management.

Although this study only investigates five neighborhood blocks in the City of Gainesville, the presented method is applicable for other urban centers when more digitalized curb environment and uses data become available. While emerging vehicular technologies and innovative mobility services (e.g., MoD) are expected to offer safer, greener, and more efficient travel services, it is of equal importance to ensure that the curb environment can accommodate the consequential changes in residents' traveling behaviors resulting from the technological and service innovations. Failure to do so may hinder the adoption and promotion of these technologies in the early stage and impede efforts towards their social, environmental, and transportation benefits (e.g., reduced traffic congestions and pollution). Our proposed methodology encoded in the case study should prepare city managers with proactive and evidence-based management tools for these transformative technologies.

Second, this research also contributes to novel practical frameworks of managing urban facilities and assets in the context of Smart City-Digital Twin as emerging digital footprints are produced by physical sensors (i.e., parking meters) and human sensors (i.e., mobile phone GPS devices) (e.g., Wang et al. 2019, 2020).

Third, we focus on the public space uses at curbs without using a microscopic traffic model for assessing curbside usage as we do not intend to address the traffic aspects of the problem. Also, existing Traffic Analysis Zone-level models fail to support policymaking at refined spatial scales to address emerging transportation problems (e.g., chaotic curb uses) introduced by disruptive transportation models (ride-hailing services and AVs) (Swarup 2021). Our research addresses this research gap by providing block level allocation strategies and supporting refined decision-making, which advances strategies at coarse spatial scales.

The research is not without limitations. Some assumptions for the agent-based simulation are case-specific and must be updated when applied in different environmental and policy contexts. Specifically, we assumed no ridesharing when visiting the POIs due to the diversity of origin/destination locations for visitors to these urban cores. This may not be true if we investigate other locations e.g., city business centers where co-workers share rides. We employed this assumption to use the aggregated visitation frequencies of POIs (by individual persons) in the studied blocks to approximate the overall interests (measured by the number of vehicles) of the blocks. We focused on the dominant MoD service, e.g., PUDO, in the simulation, while the projected MoD in different areas may consist of heterogeneous MoD services that are characterized by different needs for curb spaces and dwell time such as shared e-scooters and shared bike system. Future research may consider heterogeneous MoD services in localized curb environment management. Our developed data-driven ABM can also be tuned for simulations in curb planning for other MoD scenarios. Second, some assumptions can also be updated to include long-term urban land use and transportation changes or different facility allocations in the future. However, urban land use usually changes very slowly and is associated with different new planning policies. As we only anticipate situations in the near future, we only conduct ABS based on the most recent and best-available information. Third, we developed the data-driven ABS framework for city managers' convenience and assumed the pricing is standard hourly prices *across* curbside parking spaces in urban cores and the parking time limit for a street remains the same for future decades. Differences in parking prices across distinct curbside areas or based on demands will provide different curb uses patterns. Since we studied the localized curb uses at the street block level, we did not consider potential impacts of parking prices and time limits, which require spatial analyses at a larger scale (e.g., people may park at Block #1 instead of Block #2 even if their destination is in Block #2 just because the parking price is lower). Competition mechanisms in curb use can also be introduced (Wu et al. 2020). Fourth, similar to the limitations in the most "predict-and-plan" research, currently, we are not able to compare the outcomes of the developed ABS with future ground truth. However, this case study has offered the best "guess" of curb use situations in the studied urban cores with simulations conducted across scenarios (i.e., different market penetration rate of MoD) and sensitivity analyses whose parameters are derived from the best-available real-world longitudinal visitation and parking datasets as well as local built environment datasets and policies. All behavior patterns were retrieved from existing data over a year, including the self-parking distribution, stay time, and visitation frequency. The spatio-temporal units are small enough to shed practical outcomes for curbside management under different scenarios. With more available datasets about MoD and future market penetration and the probability to visit distinct POI, more accurate research outcomes can be derived when updating the parameters of our developed AMS model.

Conclusion

The proposed research and data-driven simulation solutions can benefit the local urban built environments in preparation for burgeoning technologies and mobility innovations. Well-coordinated curb uses have the potential to reduce on-road traffic congestion and GHG emissions, achieve safety objectives (e.g., Vision Zero), improve accessibility and well-being, and further benefit the living environment and commercial development in urban centers. In the future, data-driven curbside asset management research can consider the space uses of commercial vehicles, the parking and charging needs of electric vehicles, and the emerging types of micromobility (transit, bicycles, and e-scooters), which require updating and finer-scale management strategies to coordinate space uses and regulations within a city. Future smart curb management should also consider the special needs of the disabled population, elderly persons, and pregnant women to provide more equitable access to well-being places. This management can also leverage a cyber-physical system that integrates cyberinfrastructure (in the form of sensors, networking, data center, and mobile app) and the physical infrastructure (consisting of all available charging stations) to coordinate different curb uses requests (e.g., PUDOs or EV charging) with the aim of minimizing traveling and waiting time, alleviating congestion, reducing the environmental impact and further maximizing curb productivity and accessibility to all users. The development of real-time computing can support operations for both localized and community-wide dynamic curbside management to achieve smart, safe, and sustainable cities.

Data Availability Statement

Parking transaction data, violation data, and POI visitation frequency data used during the study were provided by a third party. Direct requests for these materials may be made to the provider as indicated in the Acknowledgments. Matlab and Python code generated or used during the study are available from the corresponding author upon reasonable request.

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Supplemental Materials

Figs. S1–S10 are available online in the ASCE Library (www.ascelibrary.org).

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