Computers, Environment and Urban Systems 99 (2023) 101914

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

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

Enabling smart curb management with spatiotemporal deep learning

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A R T I C L E I N F O

Keywords:
Built environment
Curb management
Graph-based deep learning
Smart cities
Scenario planning

A B S T R A C T

Curb spaces are important assets to cities. They are often used by travelers to switch transportation means, visitors to access curbside properties, and municipalities to place roadside infrastructure. The promotion of multi-modal transportation and the emergence of new mobility services have complicated both curb environments and their management. Consequently, some cities have started to explore new strategies for curb management, but lacked the anticipation on how different curb regulations and built-environment features may collectively influence curb-use patterns across user groups. We make a step toward smart curb environment by proposing a graph-based deep learning approach, i.e., MultiGCN-LSTM, to predict diverse curb uses across time and space. We used two graph convolution layers and an LSTM layer to capture the spatial, temporal, and semantic dependencies between curb regulations, built-environment semantics, and diverse curb uses. Two place-specific models were developed separately for a medium-sized college town and a metropolitan in the U.S. The effectiveness of the proposed models was validated with ablation studies and demonstrated in three scenario experiments. The research contributes to smart curb management in the face of more diversified and intensified curb uses with new mobility services and emerging vehicular technologies.

1. Introduction

Cities in developed countries, such as the U.S., have conventionally reserved plenty of spaces at the curbside to store private vehicles, which provide conveniences for customers to access roadside businesses and are essential for urban economic vitality (Biswas, Chandra, & Ghosh, 2017). However, this parking-oriented curb design becomes problematic in facing increasingly compact and densified urban environments where lands should be prioritized for human activities rather than storing vehicles (Cervero, Guerra, & Al, 2017). Correspondingly, many cities promote transit-oriented transportation planning and multi-modal mobility solutions to reduce citizens' dependencies on automobiles. The transit-oriented planning prioritizes transportation modes e.g., buses and subways, to move more goods and people around the city to ensure transportation efficiency (Cervero et al., 2017; Roe & Toocheck, 2017). These transit-oriented developments have nourished shared micro-mobility services, e.g., shared bikes and e-scooters, which provide first- and last-mile solutions for transit trips (Abduljabbar, Liyanage, & Dia, 2021; Zuo, Wei, Chen, & Zhang, 2020). Many cities have also renovated curb spaces to specify bike lanes to encourage active travel modes. Meanwhile, the growing popularity of e-commerce and door-to-door delivery turns transportation services into tradeable commodities, which also reduces city residents' reliance on private vehicles (Shaheen, Cohen, Yelchuru, Sarkhili, & Hamilton, 2017).

These transportation planning practices and mobility innovations have changed the way how city residents travel across the city and use curb spaces. Curbs, defined as the spaces between roadways and sidewalks (Fig. 1) (Eros, 2019; ITF, 2018), are conventionally used to separate pedestrian and vehicular traffic and serve as the frontage for people to switch transportation tools or access curbside commercial properties (ITF, 2018; Marsden, Docherty, & Dowling, 2020). Now curbs are also used by mobility service providers to place facilities (e.g., shared bikes, e-scooters, EV charging stations), ride-hailing clients to wait and complete the transactions, deliveryman to pick-up and drop-off the goods among other demands (Jaller, Rodier, Zhang, Lin, & Lewis, 2021). The more intensified and diversified uses of urban curb spaces require a

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https://doi.org/10.1016/j.compenvurbsys.2022.101914
Received 21 March 2022; Received in revised form 9 September 2022; Accepted 7 November 2022
Available online 16 November 2022

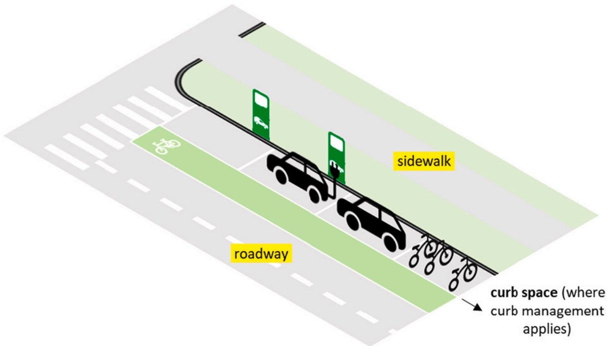

Fig. 1. Illustration of Curb Spaces.

nuanced understanding of curb uses across time and space to better accommodate different user groups. Failure to achieve this may lead to negative impacts ranging from space usage conflicts, roadway traffic congestion, increased environmental emissions, to degraded revenues for curbside businesses (Jaller et al., 2021; Wang, Hao, & Wang, 2022; Yu & Bayram, 2021).

To mitigate the undesired consequences, some cities have started to explore novel strategies for allocating and regulating curb spaces (i.e., curb management), such as designating pick-up drop-off (PUDO) zones and implementing time-variant parking regulations (Butrina, Le Vine, Henao, Sperling, & Young, 2020; ITF, 2018; Nichols & Dorsett, 2022; Roe & Toocheck, 2017; Rosenblum, Hudson, & Ben-Joseph, 2020). However, the decision-making on where and when should these curb management strategies be adopted is often *reactive* without systematically evaluating the spatio-temporal dynamics of diverse curb uses (Butrina et al., 2020; Zalewski, Buckley, & Weinberger, 2012), which may yield inconsiderate actions and inconsistent policies.

The systematic evaluation of the diverse curb uses can be challenging. First, the spatio-temporal distributions of diverse curb uses are dependent on surrounding built-environment features, such as the availability of certain mobility facilities (e.g., sidewalks and bus stops) and the presence of functional properties (e.g., theaters and groceries). These built-environment semantic features influence the number of visitors and how they approach and use curbs. Second, the curb use patterns among different curbs are also spatiotemporally related. For example, a driver may cruise to nearby curbs when noticing that the parking spaces are fully occupied. Third, within a curb, the demand for one type of usage (e.g., private parking) is related to other uses (e.g., ride-hailing, shared micro-mobility). Consequently, the curb management strategies targeted for a specific curb use and at a particular location also influence the demands of other curb uses and at nearby curbs. Though some recent studies proposed simulation-based approaches to assist curb management (Jaller et al., 2021; Wang et al., 2022; Yu & Bayram, 2021), they may fall short in capturing the complex spatial, temporal, and semantic dependencies of diverse curb uses.

Thus, to address the research gaps, we propose a spatio-temporal deep learning approach to assist the planning and management of curb spaces. Specifically, the research has the following contributions:

- We developed a Multi-Graph Convolutional Neural Network embedded Long-Short Term Memory (MultiGCN-LSTM) model to predict spatio-temporal dynamics of diverse uses for localized curb environments.
- The approach couples two GCNs and an LSTM layer to capture the spatial-, temporal-, and semantic- dependencies of hourly curb uses across the urban cores. Especially, the semantic GCN takes the similarities of built-environment characteristics, such as the presence of mobility facilities and functional properties, into the modeling process that enabled more robust model performance.
- We showed the model application with data collected from two distinct cases, i.e., a medium-size college town, i.e., the City of Gainesville, and a metropolitan, i.e., San Francisco. We also validated the effectiveness of the model architecture with ablation studies.
- The approach uses multi-task learning that learns the correlations between different curb uses and provides an integrated understanding of diverse curb uses. We demonstrated the multi-task learning with data collected for two types of curb uses, i.e., curbside parking and docked bike-sharing, from San Francisco.

We also demonstrated the effectiveness of the model by applying it to predict the changing curb uses under hypothesized treatments in built environments and curb regulations. The research outcomes inform smart curb management and contribute to smart and coordinated curbs proactively adapting to increasing urban mobility challenges.

2. Literature review

We synthesized previous studies that explain spatio-temporal curb uses from visitors' perspectives and approaches modeling spatio-temporal dynamics of curb uses. We also reviewed novel curb management practices that have been experimented in cities.

2.1. Built-environment and regulation factors that influence curb uses across time and space

Few studies have particularly investigated factors influencing curb uses, but it is not difficult to find that the diverse curb-use patterns are largely determined by visitor flows who access curbside properties (e.g., restaurants, banks, offices). Visitors may access their curbside locations with different travel modes (e.g., buses, private cars, micro-mobility) which can occupy curbs with different spaces and temporal lengths. Many studies on travel behavior have found that travel mode choices are influenced by trip distance, travel time, trip purpose (i.e., activity), activity duration among other factors (Cheng, Chen, De Vos, Lai, & Witlox, 2019; Gong, Kanamori, & Yamamoto, 2018). Built-environment characteristics including the accessibility to various transportation facilities (e.g., bus stops), walkability, road density, built-up density, and land use also influence visitors' travel mode choices (Cheng et al., 2019; Ma, Zhang, Ding, & Wang, 2018), and thus influence the associated curb uses in destination curbs.

In addition to travel modes, the temporal distribution of curb uses is determined by visitors' trip purposes that influence their arrival time and dwelling durations. These trip purposes can be inferred from the land use or the type of visited properties (Jaller et al., 2021). For example, people park for a few minutes to pick up a coffee from the coffee store and park for more than two hours to watch movies in theaters (Gong et al., 2018; Nie et al., 2021). For commercial delivery, businesses such as supermarkets need more time for loading goods than convenience stores, while florists may require more frequent deliveries than other retailers (Allen, Anderson, Browne, & Jones, 2000). These existing studies indicate the validity of inferring diverse use demands of curb spaces based on features of surrounding built environment, such as land use, functional properties, and transportation facilities.

Additionally, the diverse curb uses are also influenced by curb regulations. For example, previous empirical studies have revealed that drivers prefer to park at curbs with lower parking rates and would cruise to those curbs at a cost of extra vehicle miles and walking distances (Gragera & Albalate, 2016; Pierce & Shoup, 2018). Temporal regulations, e.g., time-limit parking, restrict visits with longer dwell time and drive visitors to garage parking (Arnott & Rowse, 2013; Gragera & Albalate, 2016). Particularly, some cities set short time limits for curbside parking spaces to encourage frequent turn-over (Mitman, Davis, Armet, & Knopf, 2018).

All the built-environment factors and curb regulation policies reviewed in the above paragraphs can influence the spatio-temporal patterns of curb uses. However, very few data-driven studies were proposed to relate the diverse curb uses with the varied factors for the planning and management of urban curbs.

2.2. Existing statistical and machine learning models for predicting curb uses

Though not focused on curb management, some studies used statistical and machine learning approaches to predict the demands for different riderships, which influence corresponding curb uses. These studies vary in the focused riderships, spatio-temporal granularities, and selected input variables. Table 1 records different modeling approaches used in recent studies for predicting ridership demands. The majority predicted the occupancy of on-street parking spaces based on metered parking transaction records or sensors (e.g., Pu, Li, Ash, Zhu, & Wang, 2017; Zhao et al., 2021). We summarize the objectives of different studies in Table 1.

The prior research has also compared the performance of different modeling approaches (e.g., Saharan, Kumar, & Bawa, 2020) concerning spatial and/or temporal dependencies of curb uses. Generally, Geographic Weighted Regression (GWR) outperforms common statistical approaches (e.g., ordinary least square) by considering the spatial dependencies of variables in modeling the demand for ride-sourcing trips (Pu et al., 2017). Random Forest (RF) outperforms other machine learning models (e.g., support vector machine) by using the ensembling techniques and better modeling the non-linearity (Saharan et al., 2020).

Lately, an increasing number of studies have employed deep learning models to predict curb uses. For example, the coupling of Graph Neural Network (GCN) and Recurrent Neural Network (RNN), such as LSTM and Gated Recurrent Units (GRU), has been recommended by recent studies for its advances in modeling the spatio-temporal dependencies among the input and output variables (Ke, Feng, Zhu, Yang, & Ye, 2021; Zhao et al., 2021). For example, Yang, Ma, Pi, and Qian (2019) coupled the GCN and LSTM to predict parking availability with variables describing the weather and roadway traffic conditions. Zhao et al. (2021) integrated GCN and LSTM to predict real-time curbside parking availability. Particularly, the authors used two GCNs to capture the spatial proximity and semantic similarities of studied blocks. Zhao et al. (2022) also integrated GCN and LSTM to predict the short-term demands of bus trips, and geographic weighted regression is used to capture the dynamic influence of built-environment features.

These approaches contribute to more coordinated curb uses, but they are not intended for curb management and are focused on a single type of curb use. Few of them considered both temporal regulations (e.g. time-limit and meter rates) and spatial features of built environments (such as mobility facilities and functional properties). The increasingly diversified curb uses, however, require urban managers to understand the relations among different types of curb uses, curb space regulation, and the surrounding built environment.

Table 1
Approaches for modeling ridership demands.

Approach	Studies and Curb Use Type
Logistic /Linear /Poisson Regression	Saharan et al. (2020) [parking]; Fabusuyi, Twumasi-Boakye, Broaddus, Fishelson, and Hampshire (2020) [commercial delivery].
Geographic Weighted Regression (GWR)	Pu et al. (2017) [parking]; Yu and Peng (2019) [ride-sourcing]; Ma et al. (2018) [public transit].
Gaussian Mixture Model (GMM)	Nie et al. (2021) [parking].
Decision Tree (DT)/ Random Forest (RF)/ XGBoost	Saharan et al. (2020) [parking]; Yang, Heppenstall, Turner, and Comber (2020) [micro-mobility]; Ke et al. (2021) [ride-sourcing].
Multiple Perceptron Layer (MPL)	Saharan et al. (2020) [parking]; Yang et al. (2020) [micro-mobility]; Ke et al. (2021) [ride-sourcing].
Long-Short Term Memory (LSTM)	Yang et al., (2020) [micro-mobility]
(Multi)GCN-LSTM	Zhao et al. (2021) [parking]; Yang et al. (2019) [parking]; Ke et al. (2021) [ride-sourcing]; Ma, Yin, Jin, He, and Zhu (2022) [micro-mobility]; Zhao et al. (2022) [public transit]

2.3. Novel strategies for managing curb space and uses

The increasing and diversified curb uses also sparked cities to explore novel strategies, including time-variant regulation and flexible curb uses, to tackle the curb management challenges (Butrina et al., 2020; ITF, 2018; Roe & Toocheck, 2017; Rosenblum et al., 2020). An early innovative curb management program is the SF*park* launched in the city of San Francisco from 2011 to 2013. The city adjusts the rates for curbside parking spaces every few months to pursue a parking occupancy rate of 60–80%, which is considered beneficial for transportation efficiency and the environment (Millard-Ball, Weinberger, & Hampshire, 2014; Pierce & Shoup, 2018). The city of Seattle defines curb spaces as “flex zone” and adopted a city-wide prioritization framework that assigns ranked priorities for different curb uses according to land use. In New York, the city implemented the Off-Hour Deliveries (OHD) program to shift truck deliveries from peak periods to off-hours (i.e., 7 pm to 6 am) to reduce traffic congestion and double parking (Holguín-Veras, Ozbay, Kornhauser, Shorris, & Ukkusuri, 2010).

Despite these significant pilot programs for curb management, there still present many challenges for managing curb environments. First, many curb management practices are implemented in an “incremental” manner (Zalewski et al., 2012), in which cities make ad hoc adjustments on their extant curb management practices every time confronting new challenges. Such ad hoc approaches lack systematical evaluation of the curb issues and ignore the hidden correlations of different curb uses and across different curbs. Large-scale programs such as SF*park* can address this problem with abundant data collected from practices, but are conducted with a time-consuming trial-and-error process (Pierce & Shoup, 2018) and only consider individual curb use (i.e., parking). A few recent studies used simulation to examine the impacts of different curb space allocation and regulation scenarios. For example, Jaller et al. (2021) integrated macro- and micro-scopic traffic simulation tools to simulate parking behaviors of private cars, freights, and taxis in three distinct districts in San Francisco. Yu and Bayram (2021) simulated the interactions between traffic flow and different curb uses, including parking, PUDO, and commercial loading/unloading, to evaluate the effects of different curb space allocation policies. Recently, Wang et al. (2022) simulated the impacts of designated PUDO zones on mitigating curb use competitions under the projected increments of MoD market share. These simulation-based studies support systematic evaluations of curb management strategies, but they are often limited in application scope (e.g., a district or a neighborhood) and made assumptions about drivers' traveling and parking behaviors.

Given these research challenges, we propose to use MultiGCN-LSTM to predict the fine-grained spatio-temporal dynamics for different curb uses.

3. Developing MultiGCN-LSTM deep learning architecture for predicting curb uses

Though curb spaces are used for various purposes by different curb user groups. We framed the dynamics of diverse curb uses with a unified conceptual framework (Fig. 2). The framework models the diverse curb uses as a dependent variable of the spatio-temporal distribution of curb regulation and visitation patterns. The visitation patterns are further determined by nearby mobility facilities and visitors' activities that can be referred from surrounding functional properties.

The green blocks in Fig. 2 are potential input variables of the model while the orange block is the output, i.e., the dynamics of different curb uses. We used a state-of-the-art deep learning model, i.e., MultiGCN-LSTM, to realize the conceptual model shown in Fig. 2. The LSTM is

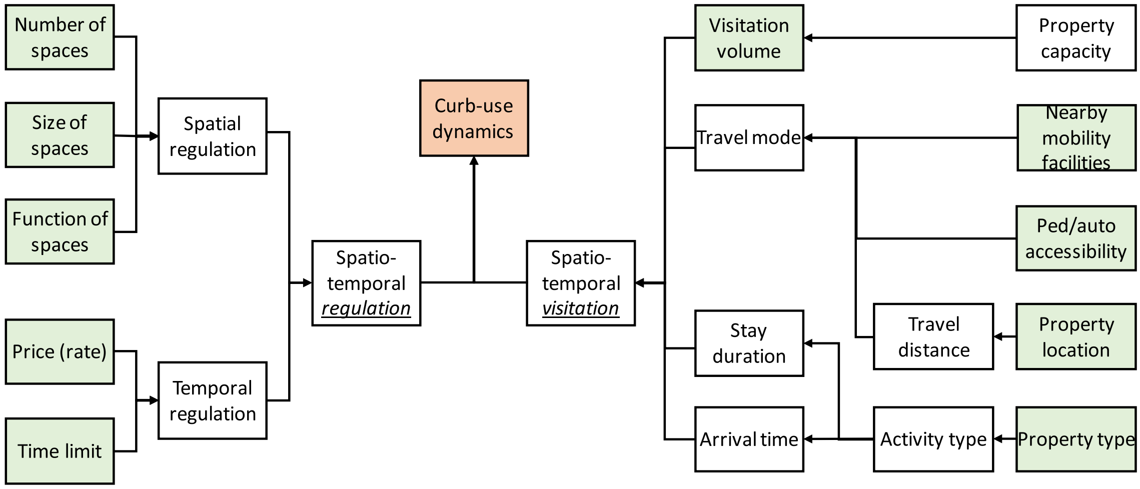

Fig. 2. The conceptual framework for modeling diverse curb uses.

suitable for modeling sequential data such as the time series of curbside parking occupation while the GCNs can process data of networked structures. The coupled approach enables the model to capture the spatial-temporal dependencies of diverse curb uses. The following definitions are given for the model development.

Definition 1. Spatial graph of curbside parking spaces.

We represent the street layouts as a connected graph, i.e., $G_p = (V, \mathrm{E}, \mathrm{A}_p)$, where V is the set of nodes and E is the set of edges. The nodes are the smallest analysis units of the graph, e.g., a curb segment or a street block. $A_p \in \mathbb{R}^{\mathrm{N}\times\mathrm{N}}$ is the adjacency matrix, where $\mathrm{A_p}^{\mathrm{i,j}}$ stores the spatial proximity information between nodes i and j.

Definition 2. Semantic graph of curbside parking spaces.

Similar to the spatial graph, we used a graph, $G_s = (V, E, A_s)$, to represent the semantic proximity among different nodes. The $A_s{}^{i,j}$ stores the similarity metric between two nodes i and j regarding localized built-environmental semantics.

Definition 3. Vector representation of functional properties.

We represent the set of functional properties (i.e., Point of Interests or POIs) within a street block as an L dimension vector $p \in \mathbb{R}^L$, where L is the number of categories of functional properties and p_i stores the number of functional properties of category i within the block. If the analysis unit is the curb segment, curb segments of the same street block share the same functional property vector.

Definition 4. Input variables.

The input variables $X_t \in \mathbb{R}^{N\times I}$ are used to describe the spatio-temporal variables related to the N nodes at time t, where I is the number of input features, e.g., meter hourly rates and visitation volumes.

Definition 5. Output variable.

The output variable, $\hat{o}_t \in \mathbb{R}^{\mathrm{N*k}}$, are the predicted k different curb uses

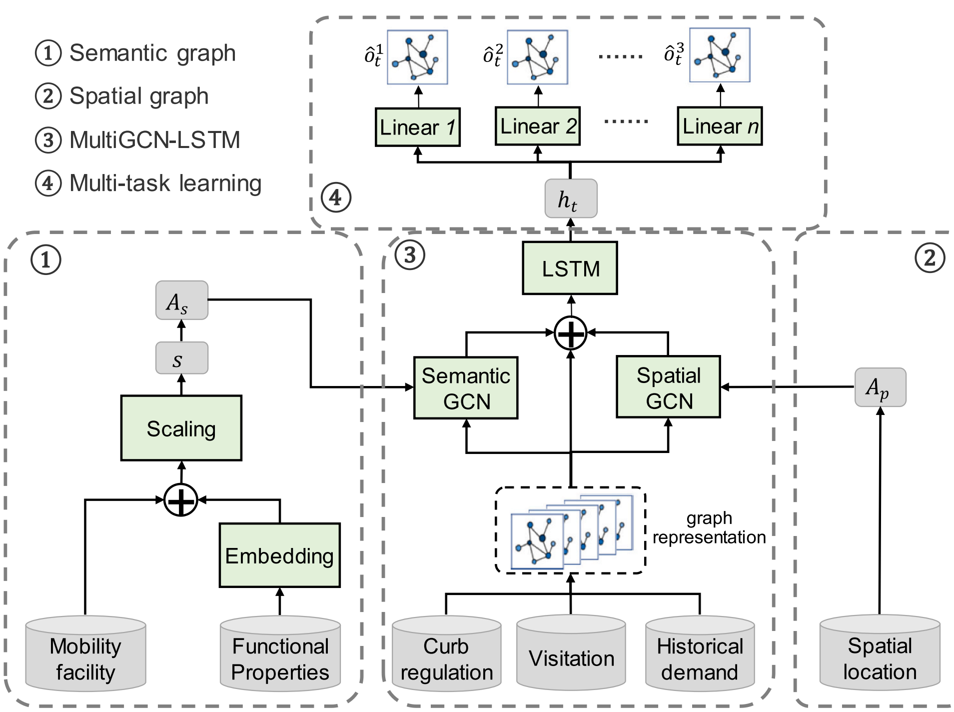

Fig. 3. The architecture of the MultiGCN-LSTM model.

and for N nodes at time t, while the actual curb uses are represented as $o_t \in \mathbb{R}^{N*k}$.

With these definitions, the problem is formulated as learning a model f to predict the diverse curb uses for the next T' timesteps based on input variables of before T timesteps (Eq. 1).

$$f(G_p; G_s; [X_{t-T+1}, \dots, X_t]) = [\widehat{o}_{t+1}, \dots, \widehat{o}_{t+T'}] \tag{1}$$

Fig. 3 shows the structure of the MultiGCN-LSTM model. The input variables describe the spaito-temporal regulations for different curb uses, previous curb uses, and visitation flows, which are organized into matrices for graph convolutions. We used two graph operations to transform the raw inputs, i.e., the spatial GCN and semantic GCN. Eq. (2) shows the formula for graph convolution (Kipf & Welling, 2016). The multiplication of raw inputs and adjacency matrices allows the integration of localized signals that are spatially or semantically proximate and learn shared weights, θ, across all nodes. In this study, the spatial proximity is determined with Eq. (3), where $d_{i,j}$ takes the Manhattan distance between the centroid of two street blocks i and j when street blocks are the analysis units. When curb segments are the analysis units, $d_{i,j}$ is calculated as the distance along the road network. The d_{thre} represents the maximum distance that a visitor is willing to walk to their destinations after parking their vehicles. We used $d_{thre} = 400m$ in this study.

$$g_\theta(X, A) = \sigma\left(\widetilde{A}X\theta\right)$$

$$\widetilde{A} = D^{-\frac{1}{2}}(A+I)D^{-1/2} \tag{2}$$

$$A_p^{\,i,j} = \begin{cases} 0 \text{ if } d_{i,j} \geq d_{thre} \\ \left(\dfrac{d_{thre} - d_{i,j}}{d_{thre}}\right)^\alpha \text{ if } d_{i,j} < d_{thre} \end{cases} \tag{3}$$

The process of determining the adjacency matrix for the semantic graph, i.e., A_s, is shown in Fig. 3 and Eq. (4). The A_s is determined as the pair-wise similarities of semantic vectors associated with each analysis unit, where the semantic vector is the concatenation of the mobility facility vector and the embedding of the functional property vector. For the mobility facility vector, we counted the presence and/or capacity of nearby mobility facilities (e.g., bus stops or parking garages). We used the vector representation of functional properties described in **Definition 3**. As there can be dozens of property categories and a street block may only include a few of them, we used a trainable embedding layer to project the long and sparse functional property vectors into dense embeddings. The scaling layer then applies element-wise multiplication for s_i with a learnable vector v_s. The purpose of this step is to increase or decrease the variances of different semantic features. The semantic similarity between two nodes is calculated as the inverse of the Euclidean distance between s_i and s_j (Eq. 4). In this way, semantic features with higher variances have more influence on determining A_s. The addition of 1 in the denominator converts the similarity metric into the range of 0 to 1 (Eq. 4).

$$s_i^{'} = s_{mobility} \bigoplus embed\left(s_{property}\right)$$

$$s_i = s_i \odot v_s$$

$$A_s^{\,i,j} = \frac{1}{\left(\left\|s_i - s_j\right\|_2^2 + 1\right)} \tag{4}$$

The two transformed matrices are concatenated with the raw input matrices and sent to the LSTM layer for modeling the temporal dependencies (Fig. 3). The LSTM layer learns both the long-term and short-term sequential patterns with three gates, i.e., input gate i, forget gate f, and output gate o, to control the writing, retaining, and discarding of inputs and previous information. The long- and short-term memories are stored with two state variables, i.e., cell state $\boldsymbol{c}$ and hidden state $\boldsymbol{h}$. When the LSTM is applied with the data collected for time $\boldsymbol{t}$, the cell state $\boldsymbol{c_t}$ is updated with forget gate f removing unuseful information from its previous cell state $\boldsymbol{c_{t-1}}$ and the input gate adding information from new inputs $\boldsymbol{x_t}$. The hidden state $\boldsymbol{h_t}$ is computed with the output gate to select useful information from the cell state $\boldsymbol{c_t}$ for output. This process is performed recursively with the new inputs. Eq. (5) shows the formula for LSTM gates and states.

$$\begin{gathered} i_t = \sigma(W_i \cdot [x_t, h_{t-1}] + b_i) \\ f_t = \sigma(W_f \cdot [x_t, h_{t-1}] + b_f) \\ o_t = \sigma(W_o \cdot [x_t, h_{t-1}] + b_o) \\ c_t = f_t \bigodot c_{t-1} + i_t \bigodot tanh(W_c[x_t, h_{t-1}] + b_c) \\ h_t = o_t \bigodot tanh(c_t) \end{gathered} \tag{5}$$

4. Case description and data collection

We developed two MultiGCN-LSTM models with data collected from two case studies, i.e., the urban core of San Francisco, CA, and the City of Gainesville, FL, respectively (Fig. 3). San Francisco (SF) is a metropolitan that has implemented multiple pilot programs to respond to emerging mobility challenges. The city has also experienced a rapid expansion of new mobility services in the past decade and is nominated as one of the best cities for living without a car (LawnStarter, 2021). Gainesville (GNV) is a med-size college town where the Univerity of Florida (UF) locates. The community increasingly adopts multiple smart mobility solutions including shared e-scooters, autonomous vehicle shuttles, and EVs (City of Gainesville, 2020). The use of these two distinct cases can demonstrate the applicability of our approach to different cities.

We considered two specific curb uses, i.e., curbside parking and docked bike-sharing for the SF case, and only curbside parking for the GNV case due to data availability. We collected data corresponding to the green blocks of the proposed conceptual framework (Fig. 3), including curb uses, regulations, and surrounding mobility facilities and functional properties, for the two study cases. Table 2 and Fig. 4 present the type and distribution of the collected data. The following paragraphs describe the data collection and processing steps.

Table 2
The various curbside mobility infrastructure in the studied regions.

Data Category	Data	Case	Description
Number and function of curb spaces	On-street parking	SF	18,448 parking meters in 833 street blocks
		GNV	314 parking meters at 42 curb segments
	Bike-share stations	SF	85 stations with 2193 spaces for docked (e)-bikes
	Car-share stations	SF	50 spots
Curb temporal regulation	Meter rates	SF, GNV	Meter regulation policy
	Meter time-limits	SF, GNV	Meter regulation policy
Visitor volume	Visitor volume	GNV	Hourly foot traffic associated with each POI
Nearby mobility facilities	Bus stops	SF	519 bus stops
		GNV	56 bus stops
	Off-street parking lots/garages	SF	12 public parking lots/garages
		GNV	10 public parking lots/garages
	Bike racks	SF	1176 bike racks
		GNV	94 bike racks
Ped/auto accessibility	Sidewalk	GNV	Block-level sidewalk coverage
Property location	POI location	SF, GNV	Spatial coordinates
Property type	POI categories	SF	9302 POIs in 130 categories
		GNV	93 POIs in 30 categories

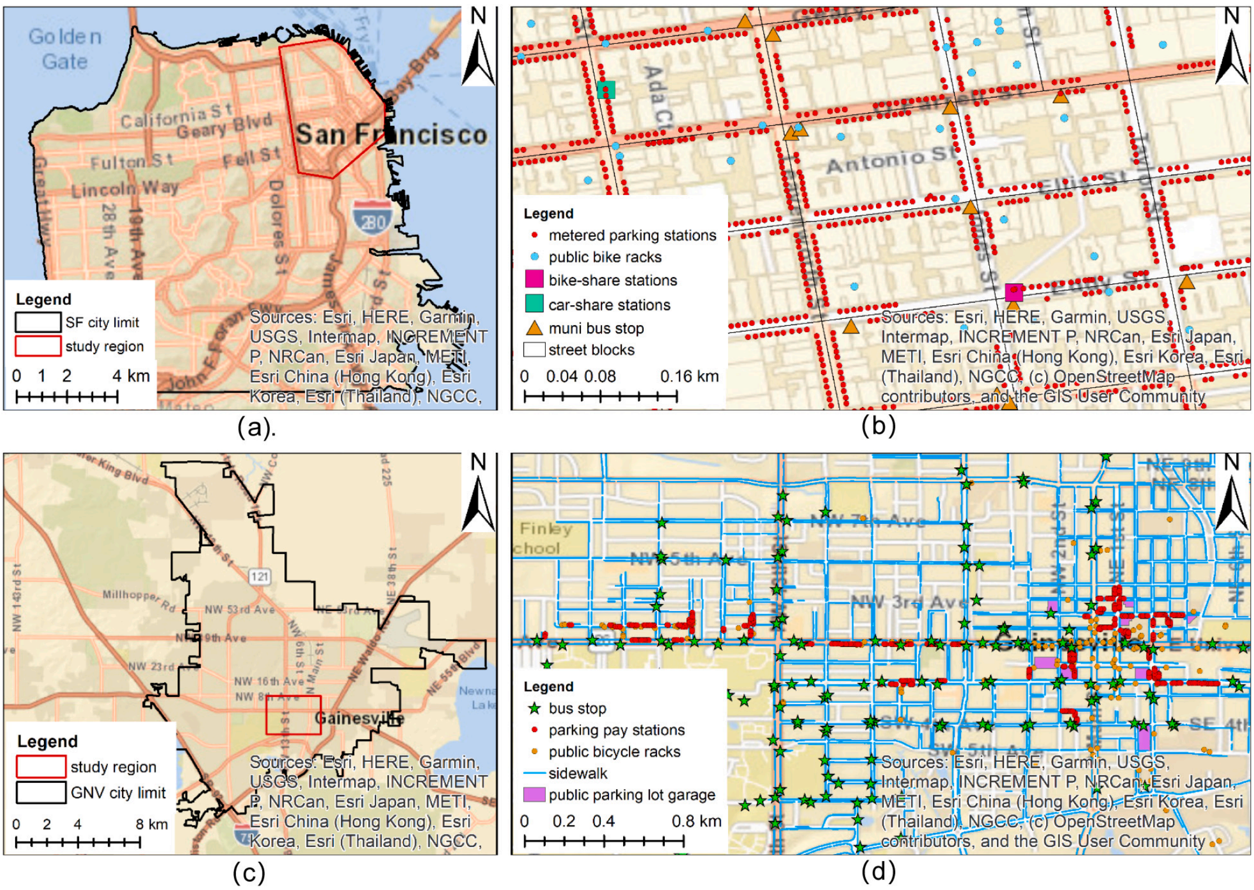

Fig. 4. The study region and the spatial distribution of mobility facilities in San Francisco (a) and (b) and Gainesville (c) and (d).

4.1. Curb use data

To some extent, the curb uses of shared micro-mobilities (e.g., bikes and e-scooters) and curbside parking are dependent, e.g., the increasing adoption of micro-mobilities can reduce city residents' reliances on private vehicles by providing alternative transportation means for short-distance trips and offering first/last-mile connections to transit passengers. We collected data for two types of curb uses, i.e., curbside parking and (e-)bike-sharing, for the SF case. Specifically, we used the metered parking transaction records to refer to the curbside parking occupations (DataSF, 2022a). Each transaction record consists of the start time and end time for a parking session and a meter ID indicating the specific parking space. We also collected the bike-sharing data from Bay Wheel (Lyft, 2022), which dominates the market share of shared (e-)bikes in San Francisco (SF Environment, 2022). The company publishes the trip data every month. Each trip record includes the start and end time and the station ID of the origin and destination for docked (e-)bikes (Lyft, 2022). For dockless bikes, the spatial coordinates of the origin and destination are provided in a much coarser resolution for privacy protection, which can not be mapped in street blocks and were hence not used in this study.

We collected one-year data from December, 1st, 2020 to December, 1st, 2021. We only used the data between 7:00 AM and 6:00 PM from Monday to Saturday, which has more intensive curb uses. We also aggregated the data for curb uses in street blocks by hours. As the shared-mobility systems frequently rebalance the (e-)bikes distributed in different stations, we only counted the number of (e-)bikes arriving at the destination block. For curbside parking, we counted both the arrival and departure of the parked vehicles. The final datasets used for the SF case include the curb-use patterns for 833 street blocks and 3432 operation hours.

For the GNV case, we collected the metered curbside parking data from the City of Gainesville's Transportation office. We used one-year meter transaction records from March 2019 to February 2020. Most meters charge for parking during weekdays from 9:00 AM to 5:00 PM with some meters operating for longer periods. We truncated the longer-period data to the normal work time and aggregated parking transaction records in curb segments and by hours. The final dataset includes the parking occupations for 42 curbside parking sites and 2349 weekday working hours.

4.2. Curb regulation data

San Francisco adopts time-variant regulations, including the pricing and time limit, for metered parking spaces (DataSF, 2022b). We matched the dynamic regulations for different curbside parking meters and aggregated them in street blocks and hourly bins. The pricing for shared mobilities is mainly determined by the traveling distances and membership subscriptions that do not relate to the curb use at the destination curbs. Hence, we did not include the pricing regulations for shared mobilities in our model. For the GNV case, though spatial disparities exist for the rates and time limits of different curbside parking spaces, the rates and time limits for individual meters are time-invariant.

4.3. Block semantic Data - curbside facilities

We collected the geo-spatial data of curbside facilities for the two cities from cities' open data portals (DataSF, 2022a.; DataGNV, 2022), including locations of bus stops, public bike racks, off-street public parking lots/garages, sidewalks, car-share stations among others (Fig. 4). We aggregate these mobility facilities into block levels.

4.4. Block semantic data – functional properties

The visiting pattern of a block, including arrival time and stay durations, is influenced by visitors' activities that can be inferred from the types of functional properties located within the block. We refer to the POI data collected by SafeGraph for the location and category of functional properties (SafeGraph, 2020). Each record includes a unique ID indicating a specific POI, together with its spatial coordinates and categories (Table 2).

4.5. Visitation flow data

We collected the foot traffic data for the study regions for the GNV case from the SafeGraph platform (SafeGraph, 2022). The data includes the hourly visitation flows for different POIs. We aggregate the visitations to street blocks through the unique POI ID shared by the foot traffic data and geospatial data. We did not obtain the foot traffic data for the SF case.

Other spatio-temporal variables, e.g., weather conditions, also influence activity frequencies and curb uses. However, those variables are not considered in the designing and regulation of curb spaces, e.g., the meter rate does not vary by weather conditions, and thus are excluded in this study.

5. Model development and validation

We developed two place-specific models for the two study cases with PyTorch (Paszke et al., 2019). We used the Adam optimizer for model parameter learning, mean square error (MSE) loss for the loss reduction, and ReLU for the activation function. We set the time length for the LSTM layer to be 12 and the hidden nodes for different layers to be 16. As we collected one-year data for both cases, we used the first-11-months data for model training while the data of the last month for validation. We trained the two models for 100 epochs with a stepped learning rate starting from 0.02 and halves every 25 epochs. We stored the model parameters corresponding to the epochs yielding the lowest losses in the validation sets for further ablation studies and scenario experiments. This combination of hyperparameters was obtained with the trial-and-error process. "Ablation" is a technique rooted in neuroscience for understanding the role of nervous systems in controlling animals' behaviors with surgical removal of nerve tissues. When applied in neural networks, it is used to investigate the effectiveness of network layers by removing corresponding layers in model predictions with a controlled setting (Meyes, Lu, de Puiseau, & Meisen, 2019). We also used ablation studies to validate the two place-specific models developed for the study cases. Specifically, we repetitively removed the parameters corresponding to the spatial GCN, temporal GCN, and LSTM layers in the model with PyTorch's pruning function. The performances of the original and "pruned" models, evaluated with Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), are listed in Table 3 and Table 4. The results suggest that both the spatial and semantic GCNs (shown in Fig. 3) contribute to higher prediction accuracy of the models. The removal of semantic GCN leads to more performance reduction compared to spatial GCN for both study cases, suggesting the importance of the built-environment semantics in determining curb uses.

Table 3
Model Performance Statistics in Validation Set, San Francisco.

Model	Curbside meter parking		Docked bike-sharing	
	RMSE	MAE	RMSE	MAE
MultiGCN-LSTM (propsoed)	2.2021	1.2367	0.4558	0.1021
Pruned model: removing embedding layer	2.2280	1.2496	0.4788	0.1099
Pruned model: removing spatial GCN	2.2273	1.2537	0.4653	0.1040
Pruned model: removing semantic GCN	7.7035	6.3488	1.7778	1.5759
Pruned model: removed LSTM	7.4745	4.2270	0.6561	0.7537

Table 4
Model Performance Statistics in Validation Set, Gainesville.

Model	Curbside meter parking	
	RMSE	MAE
MultiGCN-LSTM (propsoed)	1.1672	0.7587
Pruned model: removing spatial GCN	1.2010	0.8031
Pruned model: removing semantic GCN	1.4525	0.8815
Pruned model: removed LSTM	4.9642	2.8787

We show the spatial distribution of the actual and predicted curb-use conditions, averaged to daytime hours across the validation set, for a few example hourly periods in Fig. 5 and Fig. 6. Both figures showed that the proposed MultiGCN-LSTM model can capture the spatio-temporal dynamics of curb uses for the two study cases.

5.1. The influence of built-environment variables

One novelty of our research methodology is to include a learnable scaling layer (Fig. 3) to automatically increase and decrease the variances of different semantic variables. Semantic variables associated with higher variances have more determining influences on semantic adjacency matrice (Eq. 4), and consequently exert more influences on the prediction of curb-use conditions. Fig. 7 shows the relative importance of semantic variables considered in the two cases, where the relative importance is computed as the standard variances of the semantic variable after being projected by the scaling layer.

As there are relatively few POI categories in Gainesville, we only considered the four major categories (shown in Fig. 7a) with all others grouped as the "Other POI" category. For San Francisco, we used an embedding layer to project the 130 POI categories into 6-d dense variables that are denoted as "POI_dense_0" to "POI_dense_5" in Fig. 7(b). According to Fig. 7, the number of surrounding bus stops is the most influential built-environment factor for determining the curbside parking occupancy in Gainesville, followed by functional properties, including *Restaurants and other Eating places* and *Religious Organizations*, and the availability of nearby parking garages. For San Francisco, the different types of functional properties also played an important role in determining curb uses. Curbside transportation facilities including the number of docked bike-sharing spaces and meters also showed higher influences in predicting the curb-use patterns, possibly because the two types of curb uses are the response variables.

5.2. Demonstrative scenario experiments

We included three curb use scenarios that were tested by the two MultiGCN-LSTM models developed for SF and GNV in the **Supplementary Information (SI)** document. This section summarizes the key steps and findings of the scenario experiments.

In each scenario, we modified input variables to reflect certain changes in curb regulation or surrounding built environments and use the model to predict the curb-use patterns under hypothesized treatments. We showed that the developed models can predict the general scale of improvements for different treatments as well as associated spatial effects. Specifically, we compared how two localized treatments, i.e., designating PUDO zones and constructing a parking tower in the adjacent street block, can mitigate the shortage of curbside parking in street block #3031 in GNV. The results showed that both treatments are contributive, but constructing a new parking tower in an adjacent street block is more effective, leading to 20–50% reduction in curbside parking occupancy, compared to 15% reduction caused by designated PUDO zones (**Fig. SI-2** & **SI-3**). Both treatments not only change the curb-use patterns at "treated" curbs but also spill over the effects to surrounding curbs (**Fig. SI-2** & **SI-3**).

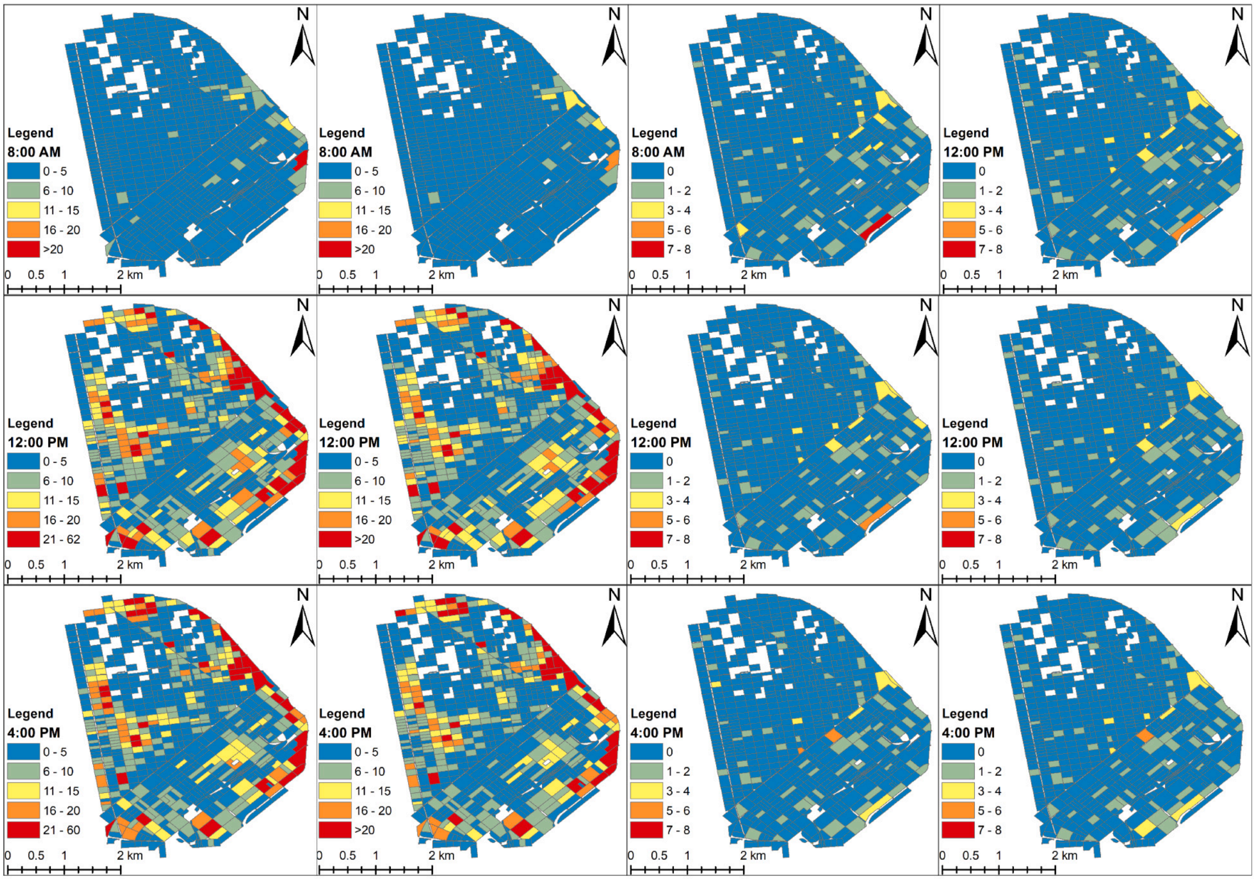

Fig. 5. The spatio-temporal distribution of actual and predicted curb uses in San Francisco.

We also compared the distribution of predicted curbside parking occupancy under static (hypothetical scenario) and dynamic meter pricing regulations in SF. The results showed that the implementation of dynamic meter pricing can produce more evenly distributed curbside parking occupations across the urban core of SF (**Fig. SI-4**). We used hot spot maps to show the differences between the predicted curbside parking occupancy under the two pricing scenarios. The results revealed that drivers tend to cruise from commercial and official centers to regions with more residential and mixed-use developments under the dynamic parking pricing scenario (**Fig. SI-5** and **Table SI-1**), which conforms with the SF*park* program's objective (Pierce & Shoup, 2018).

These demonstrative scenario experiments shed light on the usages of the developed model framework in examining the effects of different curb management strategies and built-environment improvements on curb use patterns. Notably, the results obtained from demonstrative cases are with context-specific assumptions, which a robust validation is required when applied to other scenarios and contexts.

6. Discussion

In this study, we proposed to use a state-of-the-art deep learning model, i.e., MultiGCN-LSTM, to predict the hourly demands for two curb uses (i.e., curbside parking and docked bike-sharing) at both street block and curb scales. The method is applied for two distinct study cases, i.e., the City of San Francisco, CA and Gainesville, FL that face different curb management challenges with different planned or implemented strategies. We evaluated the model against the curb use data collected from the two cases with ablation studies. We also tested the model with scenario experiments and showed that the method can quantitatively compare the effectiveness of different curb management strategies, predict the spatial spillover effects of localized treatments, and understand the changing curb-use conditions under city-wide regulations.

Recognized the challenges brought by the increasing curb activities, many cities have explored different curb management strategies and planned for various repurposing and renovation projects for curb spaces (Butrina et al., 2020; Diehl, Ranjbari, & Goodchild, 2021; ITF, 2018; Rosenblum et al., 2020). Particularly, some cities characterized their urban curb spaces as “flex zone” with dynamic regulations to prioritize different curb uses at different times (ITF, 2018). All these movements suggest more dynamic and uncertain curb environments, and a nuanced knowledge to relate the dynamic curb uses with local context is needed. Our proposed model contributes to curb management by predicting fine-grained curb-use conditions. The inclusion of semantic GCN considers the relation between the diverse curb uses and surrounding built environment features. For example, we showed that the presence of certain functional properties (e.g., Restaurants and Religious Organizations) and mobility facilities (e.g., bus stops) played an important role in influencing the on-street parking occupation in Gainesville. The use of multi-task learning also enables the predictions for diverse curb uses and gives a more integrated image of curb uses at different curbs, which helps coordinate different curb user groups.

Many cities have adopted the “incremental model” for curb management that makes adjustments to their extant curb management practices every time confronting new challenges (Butrina et al., 2020; Zalewski et al., 2012). This ad hoc planning approach can not address curb management problems systematically and may cause further issues, for example, meeting the needs of certain types of curb uses but missing others or solving the problem at one curb but burdening nearby ones. Our proposed model informs curb management practices by connecting curbs across a community and accounting for different types of curb uses

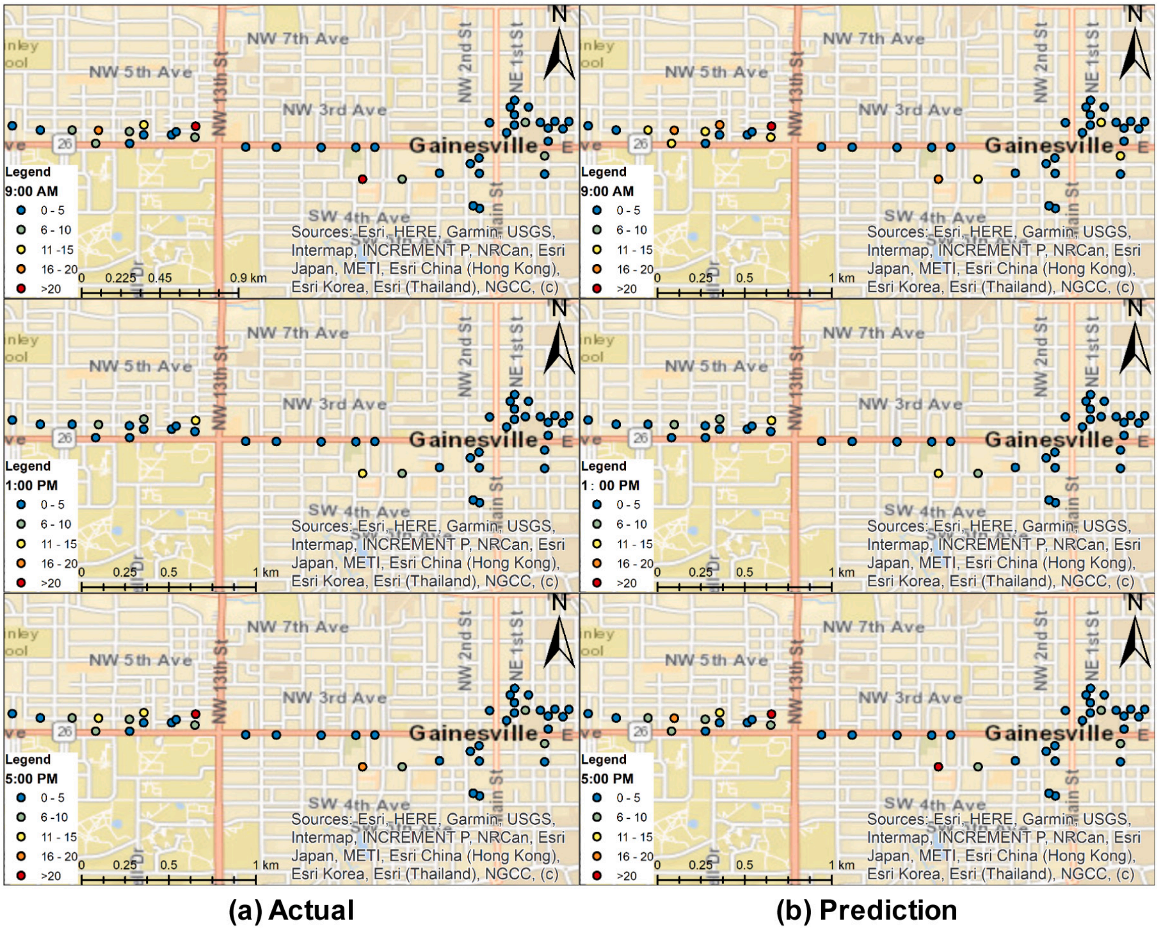

Fig. 6. The spatio-temporal distribution of actual and predicted curbside parking occupation in Gainesville.

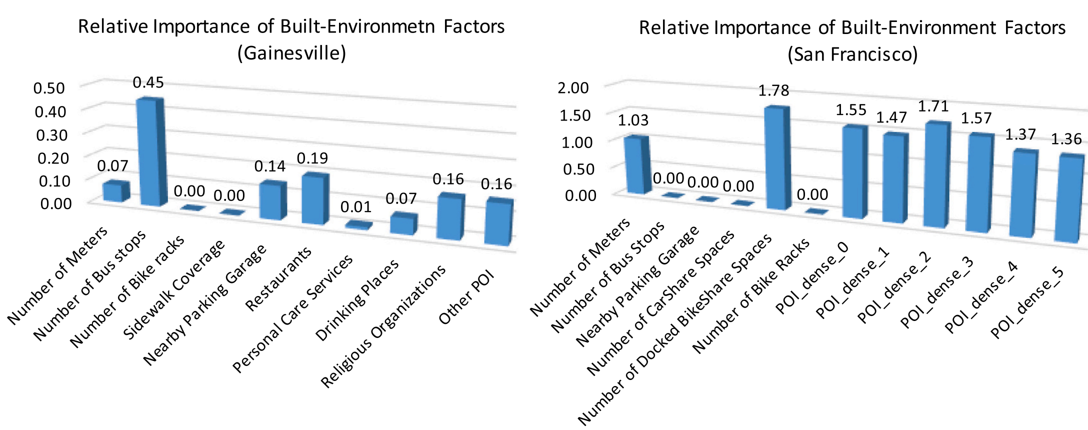

Fig. 7. The relative importance of semantic variables for two study cases.

to avoid incremental approaches in the planning and management of curb spaces.

Our calibrated deep learning model captures the spatial, temporal, and semantic dependencies among different curbs across distinct types of uses. We used scenario experiments to demonstrate that the inclusion of these complex and inherent dependencies allows models to make reasonable predictions when tested in unseen scenarios, e.g., localized built-environment changes and city-wide regulations. Such integration of deep learning models and scenario experiments suggests a potential avenue of scenario planning, which uses deep learning models to capture complex urban systems across different planning and management scenarios (Chakraborty & McMillan, 2015).

The proposed study has a few limitations that can be addressed in future studies. One limitation is the method validation. Though we have evaluated the model with ablation studies and performed scenario experiments, we were not able to compare the outcomes of model predictions with empirical observations obtained before and after a local or city-wide curb treatment. However, deep learning models allow us to anticipate distinct effects with different treatments before real deployments. In the future, we will calibrate models with the continuously collected real-world curb use data with the deployment of different treatments. Secondly, though we claimed the model can predict the diverse curb uses, we only experimented with two specific curb uses, i.e., curbside parking and docked bike-sharing, due to data availability. However, the model framework is flexible to include other curb-use data, e.g., EV charging, commercial loading, and the PUDO of shared AVs after further calibration. The proposed model would burst more usefulness when these curb uses are included due to the advantages of multi-task learning. We noticed that there are several efforts made by private and public sectors to digitalize the curb spaces and standardize curb data (Diehl et al., 2021), which supports future studies for data-driven curb management research. However, these efforts are mostly made for the supply side, i.e., what types of curb uses are permitted and how many spaces are provided (Jaller et al., 2021). Future studies may also consider monitoring the dynamic and diverse curb uses from the demand side, e.g., with advanced video analysis techniques. In addition, many other built-environment variables influencing curb uses are not considered in this research. For example, some cities have administered programs to grade the multimodal level of service for urban streets (Dowling et al., 2008). Such data can be included in the composition of the semantic graph in the developed MultiGCN-LSTM model.

7. Conclusion

The burgeoning disruptive urban technologies and new mobility services have rapidly changed the way how people live and move in cities. However, the planning and development of cities' physical built environments, e.g., curb spaces, happen at a much slower rate that does not contend with city residents' changing behaviors. The presented research suggests that cities can better accommodate their residents with effective and flexible management practices developed upon the dynamic interactions between population behaviors and urban built environments. Such spatiotemporal relations and fine-grained curb uses can be modeled and predicted with deep learning with satisfactory performance. Such data-based tools are beneficial for urban planners and transportation engineers by supporting more agile and adaptive management of urban assets in responding to various emerging urban challenges while surviving and prospering in the unpredictable future.

CRediT authorship contribution statement

Haiyan Hao: Conceptualization, Data curation, Methodology, Formal analysis, Validation, Writing – original draft, Writing – review & editing, Visualization. **Yan Wang:** Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Lili Du:** Conceptualization, Writing – review & editing, Funding acquisition. **Shigang Chen:** Funding acquisition, Writing - review & editing.

Data availability

The authors do not have permission to share data.

Acknowledgements

This material is based upon work supported by the National Science Foundation under Grant No. 2124858, the University of Florida's faculty start-up funds, and the Graduate School Fellowship Award. The authors are grateful for the parking data shared by the City of Gainesville and the POIs' visitation data shared by SafeGraph data. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation and the University of Florida.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compenvurbsys.2022.101914.

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