IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 14 September 2023, accepted 1 November 2023, date of publication 8 November 2023,
date of current version 13 November 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3331060

RESEARCH ARTICLE

Modeling the Dynamic Choice of Travel Locations With the Spatial-Temporal Bounded Rationality

CHUNJIAO DONG, JIAYU BAO, JING WANG, AND JUNYUE WANG
Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Beijing Jiaotong University, Beijing 100044, China
Corresponding author: Jiayu Bao (21120778@bjtu.edu.cn)

This work was supported in part by the Laboratory of Transport Pollution Control and Monitoring Technology, Data-Driven Dynamic Calculation of Energy Consumption and Carbon Emissions of Multiple Types Vehicles in Road Network Environment under Grant (2022)JH-F041; and in part by the Fundamental Research Funds for the Central Universities under Grant 2022RC023.

ABSTRACT It is important to understand the mechanism of travel location choices, since the dynamic individual behavior would lead to the evolution of the network. The existing location choice researches usually based on the static and perfect information, and analyzed each step of the travel independently. This research considers the interaction between individuals on a series of trips in the travel chain by incorporating the spatial-temporal bounded rationality estimation. The Indifference Zone and information sharing in the travel process are defined to explore the spatial and temporal sides. A within-day location choice model is developed based on the spatial benefit and temporal cost. The proposed spatial-temporal bounded rationality LSTM model is verified in five cities networks in China, and it shows the 8.65% and 20.30% improvement, respectively, compared to the spatial bounded rationality LSTM models and perfect rationality LSTM models. In addition, the improvement becomes more pronounced when more alternative locations (the largest city improve 31.65%), more serious congestion (improve 27.45%), more complex chain (improve 13.85%), and more stable weight (improve 22.88%). The proposed dynamic decision model with bounded rationality would provide insights for travel chain prediction in the complex urban network.

INDEX TERMS Location choice, bounded rationality, indifference zone, information sharing, within-day travel.

I. INTRODUCTION

Dynamic location decision-making is an important part of the travel chain, which is related to the accurate analysis of the nature and complexity of travel activities. In the process of travel activities, individual location decision and selection behavior often lead to the evolution of spatial-temporal distribution characteristics of network traffic flow. It is helpful for traffic planners and managers to make scientific traffic organization plans and management measures by studying individual location decision and choice behavior and clarifying the influence mechanism of location choices during travel activities.

Most existing location choices researches analyze each trip independently, applying classical utility maximum functions to provide a behavioral basis for gravity, entropy, and other spatial interaction models. It is assumed that an individual allocates a travel budget, visits the area with a specific frequency that has spatial benefit, and maximizes the total utility obtained from the visits. The interactive pattern of 'instantaneous simultaneous' location choice is achieved as simultaneous decisions. However, when attempting to realistically represent individual travel patterns, the complexity of the model increases rapidly, and even analytical solutions are not available. Even so, the discreteness of individual travel choices is usually ignored, and there is a lack of consideration of possible interactions among choices made by individuals in a series of steps in the travel chain [1]. In addition, most of the existing travel decision selection models focus on static and perfect information, and few research modeled the choice decision behavior for dynamic, bounded rationality (BR) or perceptual heterogeneity.

The associate editor coordinating the review of this manuscript and approving it for publication was Yanli Xu.

Aiming to address the gaps in the literature, this paper proposes a dynamic location choices model. The spatial benefit based on the Indifference Zone and the temporal cost based on the information sharing are considered in the BR estimation with realistic user behavior and network dynamics. It is assumed that when travelers choose the location, the total utility function is affected by the travel spatial benefit and temporal cost. In particular, the following contributions are highlighted (comprehensive literature reviews on individual topics are provided in Section II).

(1) Dynamic decision-making under multi-step travel chain. A few studies have recognized that individuals' perception of the expected utility of locations may vary dynamically, but it's hard to measure people exhibit inertia in their decision-making. This paper delves further into investigating the inception-to-end inertia throughout the travel process, considering the influence of the previously visited places and the departure time. The established dynamic decision-making model aims to capture the step-by-step progression of location selection during travel activities.

(2) Utility expression incorporating temporal elements. Current literature on location choices has primarily focused on travelers' learning and decision-making processes, often employing static daily representations to simplify the selection process. The decision-making process discussed in this paper considers the aforementioned factors as time-dependent variables and regard travel utility as spatial benefit and temporal cost two parts.

(3) Location choice model extension with BR mechanism. Most of the existing research paying less attention to analyzing the underlying mechanism of the location choice process, the modeling of travel locations has typically assumed perfect information or rationality, resulting in deterministic within-day choices. However, the dynamics of these systems necessitate an exploration of the deviation rates arising from BR. This paper posits that travelers' location choices should be determined by two key factors: the perceived time requirement for each alternative location and the satisfaction of the time interval between departure and expected arrival.

(4) Realistic mobility in large-scale networks. While a few dynamic studies have been conducted in smaller networks, they fail to fully consider the interplay between multiple forward and backward travel steps within a day. This paper addresses these gaps, we employ the BR mechanism for describing the within-day traffic dynamics in large-scale traffic networks (e.g. the Beijing network) while capturing realistic traffic phenomena. This is crucial for analyzing real-world networks.

The remainder of this paper is organized as follows. Section II offers a review of relevant literature on location choice modelling and bounded rationality. We present the proposed travel bounded rationality estimation in Section III. Location choice model considering spatial-temporal bounded rationality is described in Section IV. The dynamic models are demonstrated on the Beijing and other five cities networks in Section V. Finally, Section VI offers some managerial insights and concluding remarks.

II. LITERATURE REVIEW

This section offers a comprehensive appraisal of prior investigations pertaining to location choices and bounded rationality, illuminating the factors and models that scholars have diligently examined. Traditionally, prevailing location choice models have rested upon the foundation of utility functions, yet the perceived expected utility of a given location is inherently dynamic, susceptible to change over time, and influenced by the already traversed destinations. Although numerous influencing factors have been identified, unraveling the intricacies surrounding location choice remains an arduous endeavor. Despite the extensive corpus of literature addressing travelers' bounded rationality in location decision-making, scant attention has been devoted to encompassing the multidimensionality of bounded rationality from both spatial and temporal vantages. Hence, it is imperative to integrate the temporal dimension within the travel utility model, enabling a more comprehensive comprehension of the variables shaping travelers' decisions and fostering enhanced precision in location choice models.

In the realm of investigating the determinants of location choices, extant scholarly works have predominantly examined two categories of influencing factors. On one hand, personal attributes, encompassing gender, age, familial circumstances, educational attainment, and annual household income, have been scrutinized. On the other hand, travel attributes, such as travel distance, purpose, mode of transportation, presence of transfers, and time requirements, have been analyzed. Huang and Levinson [2] delved into the influence of land use, road network structure, and travel axis on location choice, leveraging GPS travel data. Clifton et al. [3] explored pedestrian location choice behavior through individual traveler characteristics. Malavenda et al. [4] estimated households' location and mobility choices inside a small-size area. Hatami et al. [5] considered the non-linear associations from the urban built environment. Phan et al. [6] employed Bayesian matrix factorization to rank personal location preferences, yielding user-factor and zone-factor latent matrices.

In addition to unearthing novel factors that impact location choices, scholars have also innovated the formulation of these factors by employing alternative utility functions. Random utility maximization (RUM) theory and discrete choice models have been commonly employed to estimate the probability of location choice. Lin et al. [7] used the principles of RUM to account for the details of interactive behaviors. Notably, some studies have incorporated the inherent characteristics of the travel chain, acknowledging the influence of past travels on forthcoming ones, thus conceiving location choice as a sequential process [8]. The travel utility has been conceptualized as a recursive phenomenon, whereby the expected utility function of a traffic zone j is the sum of the utility V_j derived from directly visiting the zone and the expected utility associated with future visits subsequent to the initial visit.

Bekhor and Prashker [9] explored a closed-form model, assuming a choice process that hinges on specific land use characteristics and subsequently making more refined decisions based on geographic features.

Some researchers have delved into the realm of location choice modeling. The fundamental framework of the traditional utility-based model lies in the multinomial logit model (MNL). Leveraging the maximization of the conditional likelihood function, the MNL model allows for consistent parameter estimation in alternative samples, rendering it widely employed in discrete choice modeling [10]. Various extensions of the model have been proposed, with the generalized extreme value (GEV) class model and mixed multinomial logit (MMNL) class model [11] being the most prevalent among them. Li et al. [12] developed a random regret minimization model for variable destination-oriented path planning. By incorporating travel chain behavior into simulating location choices, the expected utility of a given place not only encompasses the anticipated utility of reaching that particular destination but also accounts for the utility of potentially arriving at adjacent locations.

Moreover, with the advent of novel technologies, such as human or vehicle-mounted GPS devices, systematic tracking of travel movements has become feasible, resulting in a proliferation of location choice model studies. Based on the temporal response of travelers' decisions, these studies can be categorized into static decisions and dynamic decisions. Existing research in travel location choice predominantly adopts a static decision approach, treating multiple decisions made within a given timeframe as having the same distribution. Consequently, the probability within the location choice model remains unaffected by varying information received over time. However, an array of research findings has demonstrated that decision-making probabilities in the domain of travel behavior may systematically change as temporal constraints evolve. Dynamic continuous decision-making processes can more effectively capture the dynamic nature of decision-making choices within the travel process. Golshani et al. [13] proposed a joint model to estimate location choices in the event of unforeseen emergencies, which directly impact spatial and temporal traffic distribution within the network.

Simultaneously, a cohort of researchers has embraced the concept of bounded rationality in travel decision-making, challenging the traditional assumption that travelers consistently opt for the option with the lowest perceived costs. It becomes apparent that due to imperfect travel information and inherent decision-making inertia, travelers do not always select the location offering the highest travel benefit—a phenomenon termed "bounded rationality" [14]. Each traveler possesses unique preferences, and the suitability of a specific location varies depending on the perceived travel time and expected travel time [15]. Numerous global studies have showcased instances where travelers deviate from the optimal solutions concerning route selection, departure time, and mode of transportation [16], [17], [18], [19], [20], [21].

Exploring this dynamic evolutionary process not only facilitates the prediction of individual travel choices but also enhances the comprehension of traffic congestion dynamics within the transportation system [22], enabling to leverage advanced travel information systems more effectively. Liu et al. [23] considered the impact of benefit changes in travel behavior and modes on flow redistribution. Researchers such as Guo et al. [24], Lou et al. [25] contend that the dynamic adjustment process, transitioning from a state of non-equilibrium to equilibrium, can be viewed as the quest for an equilibrium point. Ridwan [26] explored the concept of bounded rationality in dynamic traffic modeling using fuzzy system theory. Bogers et al. [27] proposed models to examine habitual behavior under uncertain risk and the impact of advanced travel information services on route choice. Ge and Zhou [28] put forth the bounded rational routing model, known as DUE (dynamic user equilibrium), which allows for the endogenous determination of undifferentiated intervals. Wang et al. [29] used bounded rationality (BR) to improve Demand Responsive Transit. Nonetheless, a definitive solution has yet to be provided. Han et al. [30] introduced BR-DUE (bounded rationality dynamic user equilibrium) selection models for route acquisition and departure time, employing three distinct calculation methods. The convergence and stability of BR user equilibrium have been comprehensively analyzed by Yang and Huang [31], and Ye and Yang [32].

Furthermore, there has been a growing trend in incorporating temporal factors into travel behavior models. Given the dynamic nature of the traffic environment, wherein spatial benefits and temporal costs undergo constant changes, travelers are compelled to consult real-time traffic information and adjust their travel choices accordingly. Stepwise models of travel choice, categorized into within-day, day-to-day, and doubly dynamic types, have been extensively studied. The within-day travel choice problem examines how travelers determine their departure time and location on a specific day [33]. Day-to-day travel choice predominantly focuses on how travelers adapt their travel choices based on their cumulative travel experiences over successive days [34], often employing static time-invariant flow representations to describe daily travel patterns. Some scholars gradually proposed the hybrid strategy considering temporal-spatial information to traffic prediction [35], [36]. Building upon the foundation of the daily travel selection problem, the doubly dynamic travel selection problem integrates dynamic time-varying flows to capture the evolving nature of daily travel, incorporating adjustments to travel locations and departure times based on accumulated experiences. In addition to formulating dynamic stepwise models, an increasing number of studies incorporate the temporal factor as an information attribute within the model [37], [38], [39]. These studies facilitate the sharing of commuting traffic information through various information-sharing platforms, such as travel navigation apps, social media platforms, and individual social networks [40]. Particularly noteworthy is the sharing of travel experiences among travelers with similar destinations or travel plans. When a traveler designates their travel experience time for a specific origin-destination (OD) pair as shareable, all other travelers with the same OD can access it as perceived time on the information-sharing platform. Moreover, the impact of sharing on the overall perception of travel times for a given OD becomes more pronounced as the number of travelers participating in the collective sharing increases [41]. Zhang et al. [42] further found that the number and percentage of sharers can exert a negative impact initially, followed by a positive impact on the perceived travel time cost. Sophisticated spatial choice models such as TASHA and CUSTOM have been developed, incorporating the concepts of potential path area shrinking and the dynamics of expectation [43], [44].

III. TRAVEL BOUNDED RATIONALITY ESTIMATION BASED ON SPATIAL BENEFIT AND TEMPORAL COST

A. ILLUSTRATIVE EXAMPLE

In the research, the utility is conceptualized as the spatial benefit minus by the temporal cost. Thus, the objective is to identify the location that offers the greatest benefit while incurring the least cost. Fig. 1 demonstrates the optimization process using a saddle as an illustrative example.

Under the conventional assumption of complete rationality, the optimization would entail selecting the intersection point of the maximum benefit (green line) and minimum cost (red line). This optimal solution is singular, making the optimization process challenging. However, under the spatial-temporal BR framework proposed in this paper, travelers consider the benefits within a certain range as equivalent (the area between the red dotted lines). They may then choose the intersection point with lower cost as the optimal solution, without significantly compromising the associated benefits. This approach makes the optimization process easier and more aligned with actual travel scenarios.

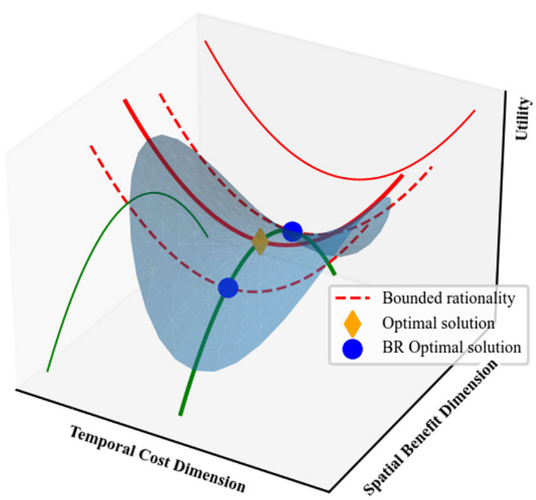

FIGURE 1. Dynamic locations choice based on bounded rationality.

B. BOUNDED RATIONALITY ESTIMATION OF SPATIAL BENEFIT BASED ON INDIFFERENCE ZONE

During the travel process, travelers face cognitive limitations in processing present and future information, making it challenging for them to become strict utility maximizers or minimizers. Furthermore, travelers exhibit behavioral inertia, preventing them from completely disregarding locations they have previously visited, which inevitably influences their decision-making behaviors. Existing studies often assume that travelers possess the ability to acquire all necessary information and make optimal decisions, thus overlooking the cognitive disparities among different decision-makers. Consequently, the cognitive process of travelers is frequently neglected in the modeling process.

In this study, spatial BR (SBR) is conceptualized as a preference that leads to non-optimal decisions based on the incomplete rationality resulting from limited access to partial information. This implies that travelers allocate fewer cognitive resources to familiar places and tend to prefer locations they have already visited. To illustrate the concept of SBR, the study area is divided into two categories of traffic zones: explored and unexplored, as depicted in Fig. 2. Explored traffic zones are those that the traveler has already visited prior to the current location, while unexplored traffic zones have not been explored by the traveler before reaching the current location. It is important to note that the classification of "explored" or "unexplored" in this paper is solely based on the studied time period. If there is additional individual knowledge beyond this period, the time scale can be adjusted accordingly for the same analysis.

Travelers exhibit a preference for choosing explored locations due to their familiarity with traffic congestion, traffic conditions, and available facilities in those areas, leading to a cognitive inertia. Consequently, the perceived benefit in explored traffic zones is higher compared to the unexplored zones, the phenomenon referred to as "benefit dependence". Therefore, when travelers explore unfamiliar locations within the traffic network, they anticipate higher travel benefits. If the benefit of an unexplored location does not surpass a certain threshold relative to the explored locations, it is considered to fall within the Indifference Zone of the travel benefit function.

To provide further insights, it is important to consider the extreme scenario wherein the traveler gradually becomes acquainted with all locations during the study period. As the traveler gains knowledge, the "benefit dependence" gradually diminishes until it reaches zero. The distinction between the Indifference Zone being exceeded or not is elucidated by (1) and (2). More comprehensive details concerning utility, individual preferences, and heterogeneity across different locations are expounded upon in Section IV.

$$\begin{aligned} &\left|\left\{U_{1,i}, U_{2,i}, U_{3,i}, \ldots, U_{i-1,i}\right\}_{\max} \right. \\ &\qquad \left. - \left\{U_{i,1}, U_{i,2}, U_{i,3}, \ldots, U_{i,n}\right\}_{\max}\right| \leq \delta_{(p,d)} \end{aligned} \tag{1}$$

$$\delta_{(p,d)} = \left|\left\{U_{1,i}, U_{2,i}, U_{3,i}, \ldots, U_{i-1,i}\right\}_{\max}\right| \times \theta_{indiff} \tag{2}$$

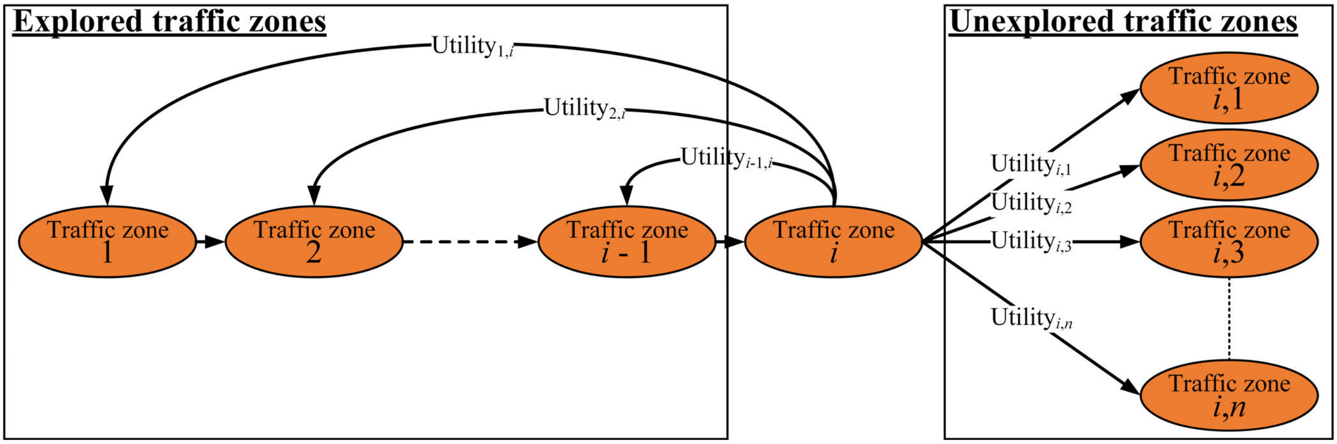

FIGURE 2. Division between explored and unexplored traffic zones.

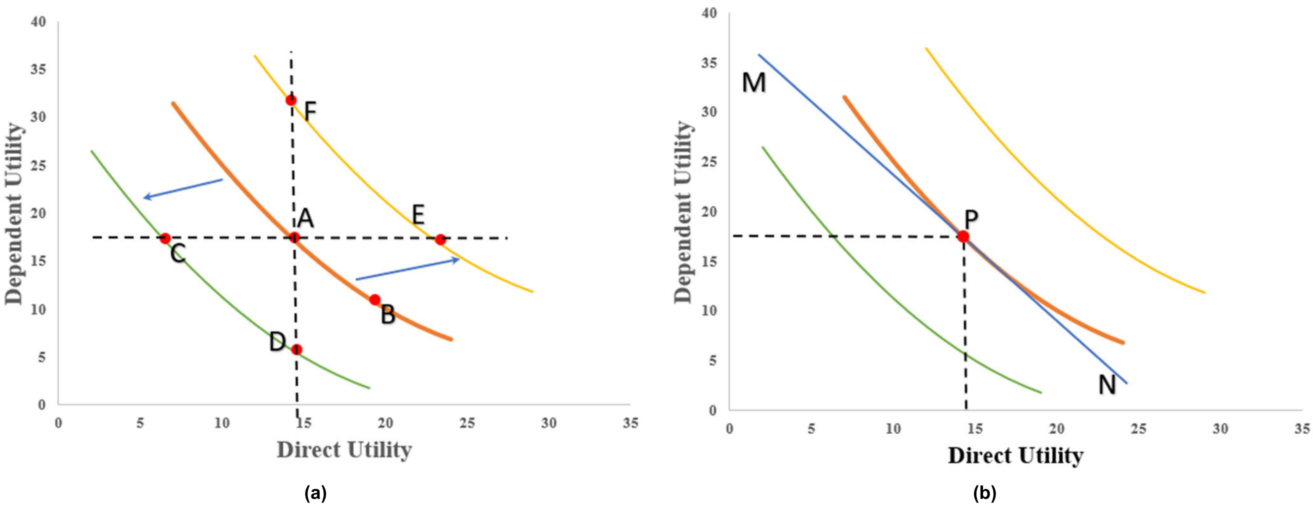

FIGURE 3. Spatial benefit based on Indifference Zone. (a) Diagram of indifference curve. (b) Equilibrium of travel utility and remaining time.

where $\delta_{(p,d)}$ is an Indifference Zone with threshold for utility of different dimensions; p, d are the parameters representing different people and dates; $U_{i,j}$ is the SBR benefit of place i and j at time t; θ_{indiff} is a proportional parameter measuring the threshold of Indifference Zone.

Therefore, the search behavior involves a balance of travel familiarity and spatial benefit. Specifically, travel benefits and travel familiarity can be represented by an indifference curve as shown in Fig. 3(a). It considers the overall utility as the sum of direct utility and dependent utility, characterized by the following features: 1) The total utility of alternative locations A and B within the Indifference Zone is equal. 2) The positions of the Indifference Zone vary across individuals, such as AB and CD. 3) When comparing locations A, C, D, E, and F, C has lower direct utility, D has lower dependent utility, E has higher direct utility, and F has higher dependent utility.

Based on the BR hypothesis, individuals make personal location choices. If location B is selected and it does not exceed the Indifference Zone of AB, location A would be preferred. However, if location E is chosen and it exceeds the Indifference Zone of AB, location E would be preferred.

Conversely, the existence of the Indifference Zone for benefits relaxes the constraint on temporal cost, leading to more location choices with the same total benefit but lower temporal cost, as illustrated in Fig. 3(b).

1) When the remaining time [45] is less than or equal to the total utility combination represented by point P (the points on line MN and below MN), the utility level does not exceed that of P.

2) If the utility level is greater than or equal to the total utility combination of P (the points on the indifference curve and all points above MN), travelers do not have sufficient travel time available.

3) The area above the right side of MN and below the left side of the indifference curve represents points where the utility level is lower than P and travelers do not have enough travel time. These locations are commonly referred to as ''inefficient and time-consuming'' travel choices.

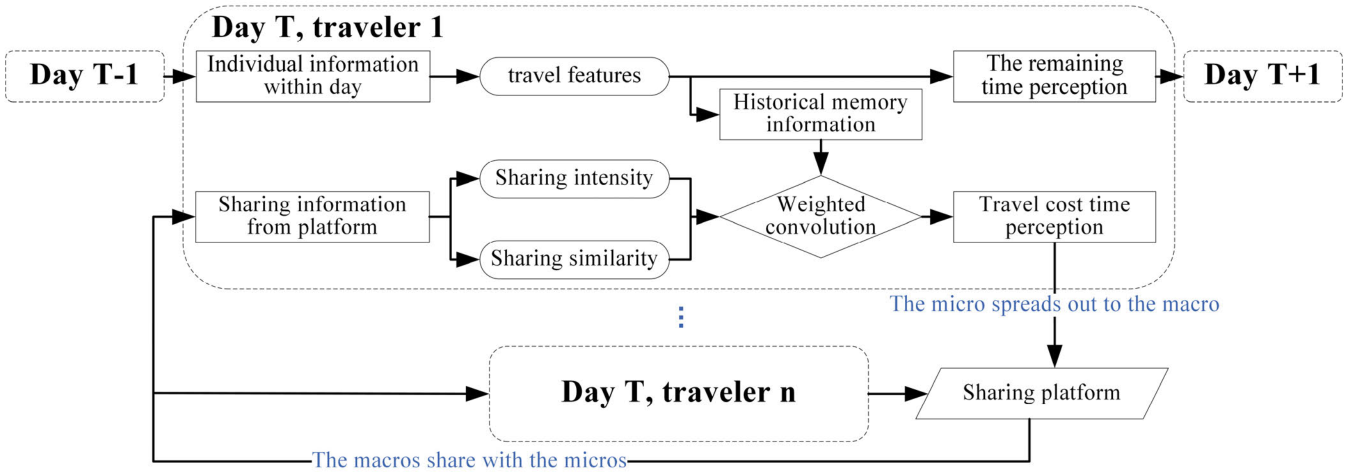

FIGURE 4. Information sharing mechanism based on temporal bounded rationality.

The width of the Indifference Zone and the threshold of BR are directly related. A wider Indifference Zone corresponds to a higher utility demand for visiting unexplored places and decreases the likelihood of travelers selecting non-visited locations.

C. BOUNDED RATIONALITY ESTIMATION OF TEMPORAL COST BASED ON INFORMATION SHARING

When making decisions about location choices, travelers are not only influenced by their familiarity with previously visited places but also affected by time-varying information such as traffic congestion, which can result in increased travel costs or reduced benefits. The mechanism of information sharing and time perception is depicted in Fig. 4. Initially, the travel cost or disutility is calculated within an individual traveler on a specific day. This cost is influenced by the traveler's own characteristics and historical travel patterns. Additionally, the traveler receives shared information from other individuals in the system, with the weight of this information determined based on its intensity and the time interval. Travelers aim to minimize their travel costs or disutility. Subsequently, the travel cost is disseminated to each traveler within the system through the operation of the transportation system, facilitated by the information sharing platform. This diffusion process ensures that travelers are informed about the overall travel costs in the system. It is important to note that in the study of within-day travel, this diffusion process only impacts travel within the same day.

In the aforementioned travel process, it considers the time-varying information sharing process as one sharing per step, the traveler will share their temporal cost experience information for the dynamic step with a group of individuals after selecting a target location in the previous step. This group consists of individuals with the same origin and destination (OD) selection in the current step. The other members of the group will utilize this shared information, multiplied by a weight factor q, to inform their perceived cost, thereby supplementing their own unknown time perceptions.

Let q represent the proportion of travelers in the group who used the OD selection from the previous step. The function $\boldsymbol{Q}$, specifying the form of the weight factor, may be nonlinear and can be defined in a piecewise manner that is directly specified or functionally fitted. By assuming $\boldsymbol{Q}$ to be monotonically increasing, it reflects the reasonable assumption that the more travelers choose the same OD selection, the higher the reliability of the information they report. Consequently, this information carries greater weight in shaping individual opinions about the OD selection. The specific form of the proportional function can be calculated using (3).

$$Q_{(w,p)}\left(\tau^{*}\right)=Q\left(\frac{f_{(w,t)}\left(\tau^{*}\right)}{\delta\tau}\right) \tag{3}$$

where w and p are the parameters to express choice, which can represent an alternative location or a person; τ is a temporal step. One choice for the proportional function is $\boldsymbol{Q}(x)=x^{n}$, $x\in[0,1]$, $n>0$.

The parameter n can be interpreted as a simplified measure of the intensity of interaction between travelers. Temporal BR (TBR) can be regarded as a dynamic game, where the process of repeated learning and decision-making by individual travelers can be further described using belief learning. Ultimately, the stable distribution of decision-making by each traveler will be influenced by the collective learning of all individuals in the system. The perception of temporal cost for the current dynamic step OD can be calculated using (4) and (5).

$$s\left(\lambda,q\right)=\sum_{n=\tau-M}^{\tau-1}q_{(w,p)}\left(n\right)\lambda^{\tau-n-1} \tag{4}$$

$$\bar{C}_{(w,p)}\left(\tau\right)=\frac{1}{s\left(\lambda,q\right)}\sum_{n=\tau-M}^{\tau-1}q_{(w,p)}\left(n\right)\lambda^{\tau-n-1}\cdot C_{(w,p)}\left(n\right) \tag{5}$$

where λ is the experience cost of the activity point in the past few steps, earlier travel has less impact on the current, so the weight in the expression is smaller; M is the number of past steps that influenced the current decision; s is the standardized factor.

IV. DYNAMIC CHOICE DECISION MODELING OF TRAVEL LOCATION CONSIDERING SPATIAL-TEMPORAL BOUNDED RATIONALITY

Travel activities arise from repeated location choices. To capture the intricacies of decision-making in travelers, the integration of spatial-temporal bounded rationality (STBR) is essential for dynamic location selection modeling within the travel process. This approach simulates the decision-making process by considering the interplay between choice preferences and information perception. The following steps outline this modeling approach:

(1) At each time step, denoted as t, the current location is categorized as either an explored traffic zone or an unexplored traffic zone, depending on whether it has been previously visited.

(2) By applying the principles of spatial benefit bounded rationality, calculate the spatial expected utility for all current locations. Identify the location with the maximum utility from both the explored and unexplored sets, respectively.

(3) Evaluate whether the maximum utility of the explored set surpasses the Indifference Zone of the maximum utility of the unexplored set. If it does, select the location from the explored set; if not, select the location from the unexplored set.

(4) Prioritize the selection set based on utility. Employ temporal cost bounded rationality to perceive the travel cost time. Assess whether the expected remaining time is satisfied. If it is, proceed to step 6); if not, proceed to step 5).

(5) Determine if the remaining locations in the standby set are non-empty. If they are, select the next location based on ranking and repeat step 4); if they are not, conclude the travel chain for the current day.

(6) Advance the travel chain by t steps, arriving at the chosen location and generating new spatial benefit and temporal cost.

(7) Proceed to the next time step, $t+1$, and return to step 1).

In order to establish an appropriate framework for the travel location selection model, this study employs a specialized architecture known as Long Short-Term Memory (LSTM) along with a mapping layer that incorporates the principles of BR. The optimization process is conducted using the versatile Adaptive Moment Estimation (Adam) method, enabling iterative learning to achieve a comprehensive simulation of travelers' decision-making processes.

The BR mapping layer encompasses the convolution operation between BR dummy variables and the eigenvalues derived from the preceding layer. The consideration of BR is primarily manifested in the mapping of the "BR dummy variable" onto the multiple choices available for alternative locations. Each location is represented by a binary dummy variable (0 or 1), indicating whether it is taken into account during the decision-making process. The selection matrix, which captures the influence of STBR, is seamlessly integrated into the multi-classification model as the component vector of random utility, described in (6). This facilitates an exploration of the impact of BR factors on location choices. The calculation of travel space benefit is determined using (7), $V_{ij}^{BR}(\boldsymbol{x})$, which is based on (1). By identifying the recommended subset that adheres to the calculations of STBR (assigned 1), while others are assigned a value of 0, can be obtained the BR features $[x_{m+1} \ldots x_{m+n-1}]$.

$$U_{ij}^{*} = V_{ij} + V_{ij}^{BR}\left(U_{ij}\right) + \varepsilon \Rightarrow [x_1 \ldots x_m] \oplus [x_{m+1} \ldots x_{m+n-1}] + \varepsilon \tag{6}$$

$$U_{ij} = \begin{cases} \dfrac{\sum_{\alpha \in A_j} m_\alpha}{\sum_{\beta \in B_j} r_\beta}, & i \neq j \\ 0, & i = j \end{cases} \tag{7}$$

where V_{ij} are conventional travel features $[x_1 \ldots x_m]$ input the deep learning network, and V_{ij}^{BR} are BR features $[x_{m+1} \ldots x_{m+n-1}]$ got by 'BR dummy variable' input the network. A_j represents a set of positive impact factors for location j, B_j represents a set of negative impact factors for location j.

The network architecture in this study encompasses various components, including Flatten, Feed Forward, Tanh & Dropout, and Softmax. These elements collectively contribute to the training process conducted within the Deep Learning network, as illustrated in Fig. 5.

Where n is the number of alternative locations within the research scope; x_i are the travel features used by the model, and m variables are taken by the model; dropout coefficient is calculated according to experience. The dimension of the first full connection layer is $[i+n\text{-}1, 2^k]$, and the dimension of the second full connection layer is $[2^k, n\text{-}1]$. For the input gate part of the Conv-LSTM layer, the i_t is calculated by (8), and the C_t is calculated from the last state C_{t-1} and the input candidate state C_t^* by (9):

$$i_t = \sigma_{BR}\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{8}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot C_t^* \tag{9}$$

where δ_{BR} is calculated by parameter $\delta_{(p,d)}$ of STBR modeling.

The Flatten operation is employed to transform the multi-dimensional travel features into a one-dimensional format. Subsequently, the fully connected layer is utilized to map and characterize the feature space, aiming to minimize the impact of irrelevant attributes on the outcomes of location choices and enhance the overall robustness of the network. Finally, the Softmax function is applied to present the results of travelers' choices for alternative locations in the form of probabilities,

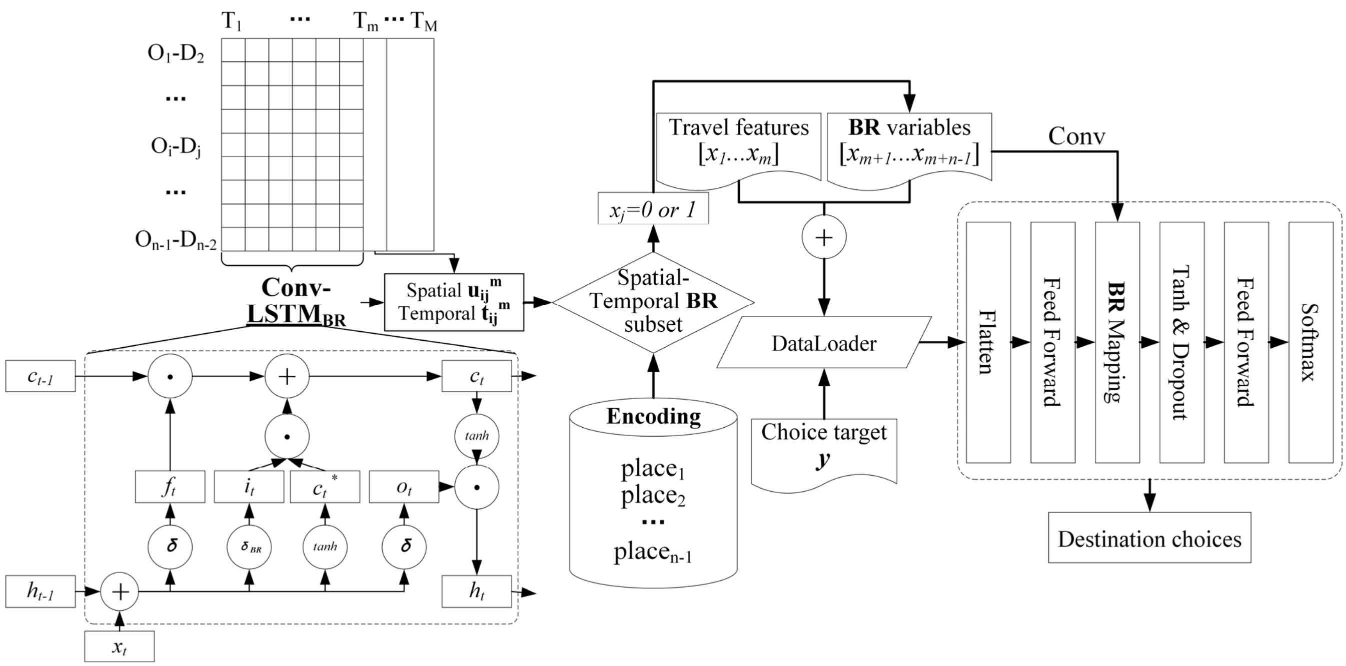

FIGURE 5. Dynamic decision mechanism of location choices.

as denoted by (10).

$$P_{soft\max}(y|x) = \frac{\exp\left(W_y \cdot x\right)}{\sum_{i=1}^{N} \exp\left(W_i \cdot x\right)} \tag{10}$$

The Tanh function is utilized as the activation function in both the LSTM gate and the FeedForward layer. The specific form of the FeedForward operation is represented by (11) and (12), which converts the input values into a range of $(-1, 1)$. This transformation, along with its derivative $(0, 1)$, helps mitigate the issue of gradient disappearance, ensuring that the relationship between travel multiple choices and influencing factors maintains a nonlinear monotonic trend. Moreover, it enhances the fault tolerance of the STBR simulation. To address the overfitting phenomenon, Dropout is employed, which disregards the interaction of partial travel features. By temporarily deactivating neuron activations with a probability p during the forward propagation of features, Dropout reduces local dependence and enhances the generalization of the BR travel model. This regularization technique promotes a more robust and adaptable framework for modeling STBR.

$$y_{ij} = \sum_{u=1}^{U} \sum_{v=1}^{V} w_{uv} x_{i-u+1,j-v+1} \tag{11}$$

$$\tanh(y_{ij}) = \frac{e^{y_{ij}} - e^{-y_{ij}}}{e^{y_{ij}} + e^{-y_{ij}}} \tag{12}$$

where x is the characteristic value of the full connection layer, and y_{ij} is the result after the mapping of BR dummy variables.

To address the imbalance in the number of alternative sites within each city in the data, the FocalLoss function (13) is employed. This function assigns weights to the loss corresponding to each location, taking into account the difficulty of distinguishing between alternative sites. By adjusting the loss weighting, the model can effectively address the challenges posed by imbalanced data and enhance its ability to differentiate between different location choices.

$$FL\left(p_i\right) = -\left(1 - p_i\right)^{\gamma} \log\left(p_i\right) \tag{13}$$

where p_i is the probability of selecting an alternative location i; γ is the focusing coefficient.

To expedite the attainment of the solution set and mitigate any performance impacts resulting from the complexity of the alternative location set, an intelligent optimizer called Adam is employed in the experimental phase. By leveraging the capabilities of Adam, the model can effectively uncover STBR factors to their fullest extent. RMSprop is utilized to optimize the gradient direction through an adaptive learning rate and momentum approach. RMSprop allows for the adjustment of the learning rate based on the current gradient situation, ensuring that the learning rate is tailored to the convergence speed of each parameter dimension. On the other hand, the momentum method ensures that the gradient correction speed at the current iteration is influenced not only by the negative gradient but also by the weighted moving average from the previous iteration. The update of parameters during the iteration is calculated using (14) and (15). These optimization techniques contribute to the efficient and effective training of the model, facilitating the exploration of

STBR factors.

$$m_t = \frac{m_t}{1-(\beta_1)^t}, v_t = \frac{v_t}{1-(\beta_2)^t} \tag{14}$$

$$\theta_t = \theta_{t-1} - \frac{m_t}{\sqrt{v_t}+\varepsilon} \cdot l_r \tag{15}$$

where l_r is learning rate; β_1 and β_2 are smoothing constants (or decay rates), which are used to smooth m and v, respectively; θ is a learnable parameter; t is the number of exercises.

To delve deeper into the structural aspects of the neural network model for BR location choices, this study will establish several experimental groups. Firstly, a perfect rationality LSTM (PR-LSTM) model without BR will serve as the control group. Secondly, a spatial bounded rationality LSTM (SBR-LSTM) model will be developed, incorporating SBR estimation. Lastly, a spatial-temporal bounded rationality LSTM (STBR-LSTM) model will be implemented, incorporating STBR estimation.

By introducing STBR, the research dimensions are expanded by predicting the end of within-day travel. Existing location prediction models often struggle to determine the stopping point of travel as they require specifying the number of predicted steps in dynamic decision-making. This limitation stems from the fact that travelers have finite time available to spend at a specific location while also considering the perceived cost of determining the optimal travel time. To address this, the concept of "expected remaining time" is introduced as a measure of travelers' willingness to continue their journey. It is calculated as the expected total travel time minus the decision time. The model sets a prediction threshold by ensuring that the temporal cost perception of all alternative locations at the decision time does not exceed the expected remaining time.

In this model, the expected remaining time takes into account the heterogeneity among different individuals, considering both subjective and objective factors. Subjective heterogeneity refers to the fact that individuals have different thresholds for the maximum tolerable time, which influences their decision-making process during current travel. The perception of time cost meeting the expected remaining time can be mathematically expressed as (16).

$$\bar{C}_{(w,p)}(\tau) \le \left(T_{(p,d)}(\tau) - t\right) \times \left[1 + r_{(w,p)}\left(\theta_{indiff}\right)\right] \tag{16}$$

where, $T_{(p,d)}$ is the expected total travel time; p, d are the parameters representing different people and dates; $r(x)$ is the proportional function of expected remaining time, which is calculated as same as $q(x)$. θ_{indiff} is a proportional parameter measuring time perception.

Objective heterogeneity is observed in various aspects, including the current location within or in the vicinity of the central business district (CBD) of the city, the size of the city itself, the timing of departure during peak or off-peak hours, and the complexity of the travel chain on a given day. These objective factors contribute to the variation in individuals' perception of time cost and further influence their decision-making process.

V. NUMERICAL CASE STUDIES

To validate the efficacy of the proposed dynamic decision selection model for travel location, which takes into account STBR. GPS data derived from vehicle trajectories in cities of varying magnitudes, including Beijing, Shanghai, Wuhan, Shenzhen, and Hangzhou, which could test for the heterogeneity mentioned in Section III. These cities' collective ability could assess the generalizability and commonalities of the model's performance in large networks. It should be noted that the administrative divisions were utilized as traffic analysis zones, enabling to simulate and replicate the individual decision-making behavior pertaining to travel location choices.

A. DATA DESCRIPTION

The original dataset consists of GPS data recorded at 30-second intervals from onboard devices. Each data entry includes various parameters such as vehicle ID, collection time, upload time, vehicle direction angle, instantaneous speed, frequency of acceleration and deceleration, longitude, latitude, administrative region, road name, and collection status.

To effectively capture the essence of BR in travel decision-making and mitigate the computational complexity, the analysis is performed at the level of urban administrative districts rather than individual GPS positions. For this study, it is selected motor vehicle data from September 23, 2019, encompassing 5,699 vehicles in Chaoyang, Beijing, 7,329 vehicles in Pudong New Area, Shanghai, 4,080 vehicles in Wuchang, Wuhan, 2,465 vehicles in Gongshu, Hangzhou, and 2,462 vehicles in Baoan, Shenzhen. Fig. 6 depicts the origins and location choices of motor vehicle travel in these five cities.

To thoroughly extract valuable insights from the GPS data of vehicle driving tracks and minimize reliance on individual traveler attributes, the model places greater emphasis on vehicle travel characteristics and alternative location characteristics. These include a range of variables, as presented in Table 1. A comprehensive analysis of travel characteristics in the five cities is illustrated in Fig. 7.

Among these variables, the number of activity points indicate travel activity. In the data, it is observed that 42.37% of trips consisted of 2 steps, while 28.92% were 3-step trips, and 28.71% involved travel chains of at least 4 steps. Notably, mega-cities such as Wuhan, Hangzhou, and Shenzhen exhibited a higher number of steps and more active travelers compared to super-cities like Beijing and Shanghai, where the percentages were 19.82%, 15.82%, and 9.43%, respectively.

The departure time and arrival time provide insights into travel peaks and concentration. Departure time peaks between 7:00 and 9:00, accounting for 15.34% of trips, while the highest arrival time occurs between 17:00 and 19:00, representing 15.26% of trips. Larger cities tend to exhibit more concentrated patterns in terms of departures and arrivals.

FIGURE 6. **Vehicle travel trajectories within the study area. (a) Chaoyang, Beijing as origin. (b) Pudong New Area, Shanghai as origin. (c) Wuchang, Wuhan as origin. (d) Baoan, Shenzhen as origin. (e) Gongshu, Hangzhou as origin.**

TABLE 1. **Summary statistics of variables in model.**

Variable name	Variable description	Mean				
		Beijing	Shanghai	Wuhan	Shenzhen	Hangzhou
Point num	Number of nodes in travel chain (stop 15 min at least).	3.89	3.64	3.79	3.48	4.47
Drive time	Total time cost between two zones.	1.20	1.67	1.01	1.41	0.98
People	Number of people in the zone.	0.38	0.33	0.36	0.30	0.49
Area	Area of the zone.	0.42	0.27	0.28	0.23	0.13
Distance	Straight-line distance traveled in the zone.	20.77	23.79	11.21	18.40	9.97
Stop start	Time when start parking in the zone.	0.39	0.36	0.44	0.38	0.45
Stop end	Time when finish parking in the zone.	0.67	0.69	0.70	0.72	0.71
Stay time	Time stays in the zone.	2.66	2.56	2.59	1.93	1.98
Stop num	Number of times a traveler stops in the zone.	2.02	1.65	1.78	1.97	1.89
Stop inter	Interval between last stay and this one	2.97	2.74	2.86	2.25	2.31
Stop inter prop	Proportion of stopping interval in the whole day's travel time	0.31	0.29	0.31	0.25	0.24

The total travel time within a day reflects the level of time cost in urban travel. Considering trips within a two-hour timeframe, larger cities demonstrate a higher percentage of trips exceeding 60 minutes, with figures of 37.14%

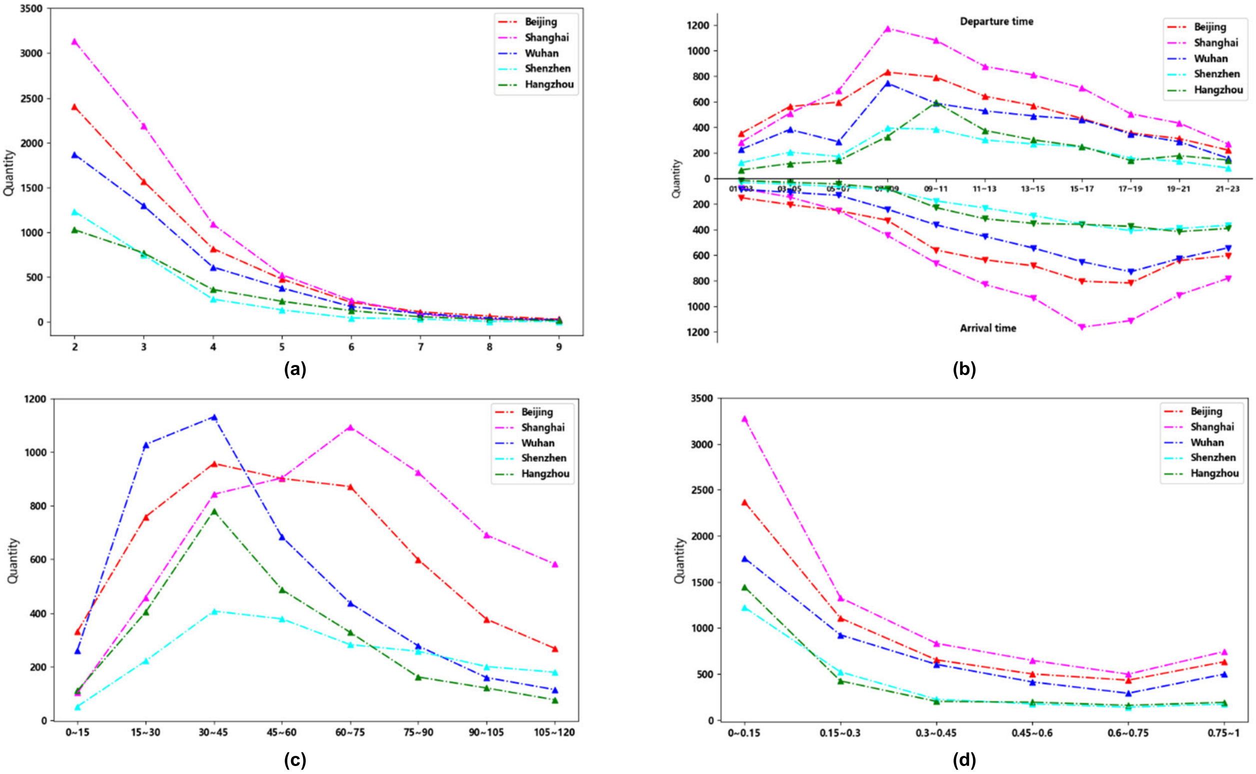

FIGURE 7. Analysis of travel characteristics in five cities. (a) Number of activity points. (b) Departure time and arrival time. (c) Total travel time within day. (d) Proportion of stopping intervals.

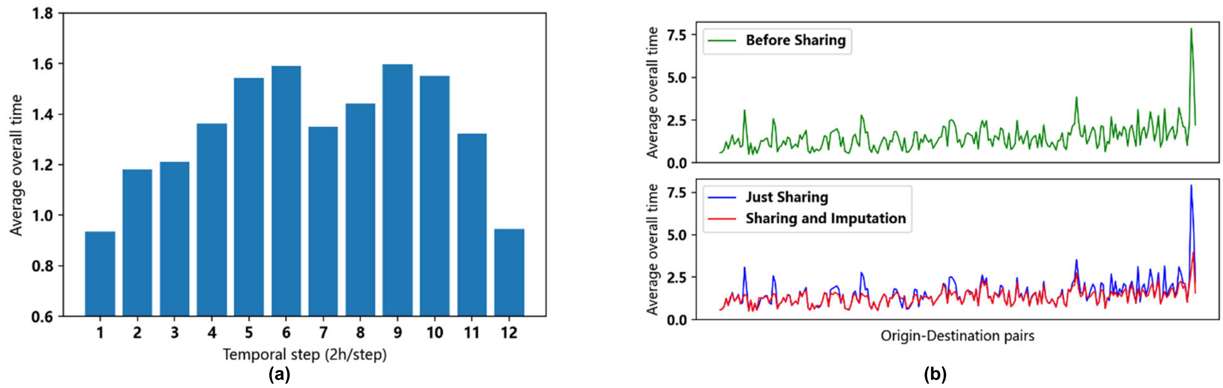

FIGURE 8. Time characteristics of neural network input data. (a) Average time of each step in zones. (b) Average time of each point in zones before and after imputation.

for Beijing and 44.94% for Shanghai. On the other hand, smaller cities exhibit a higher proportion of trips under 45 minutes, with Wuhan at 53.92% and Hangzhou at 49.39%. Shenzhen, despite its compact urban area, shows a balanced distribution of travel time due to its high built-up density.

The proportion of stopping intervals provides an indication of travel patterns. Specifically, 63.65% of common travel steps have a stopping interval proportion of less than 0.3, while 36.35% of main travel steps have a proportion greater than 0.3. Among the five cities, the percentages for Beijing, Shanghai, Wuhan, Shenzhen, and Hangzhou are 38.98%, 37.16%, 40.25%, 29.01%, and 28.59%, respectively.

B. MODEL PERFORMANCES

To facilitate smoother execution of the neural network, the experimental focus is on 2-7 step travel chains. Vehicle GPS travel data collected from Sept. 2019 to Oct. 2019 in the five selected cities are utilized. To address the issue of imbalanced classification in the target data, four days' worth of data is used to increase the number of target selections, while also controlling the number of target selections to be below 500. Furthermore, appropriate merging of administrative districts is performed.

The average duration of within-day travel in the analyzed zones, obtained through data processing, is depicted in Fig. 8(a). The morning peak period spans from 7:00 to 9:00, while the evening peak period spans from 16:30 to 19:30. Each temporal step corresponds to a 2-hour interval, and missing values are interpolated to ensure data completeness. The overall data, both before and after interpolation, is presented in Fig. 8(b). The expected latest travel time is set at 20:00.

The Indifference Zone θ_{indiff} holds significant importance when its value exceeds a certain threshold. In the bounded rational travel behavior, it is widely acknowledged that the threshold value should be below 10% [46]. Previous sensitivity experiments have been explored the reliability of this threshold, allowing for adjustments within a specific range. Different threshold values had a relatively homogeneous impact, indicating that the results were not overly sensitive to changes in the threshold. Considering the characteristics of the data examined in this paper, it is empirically analyzed the threshold value using a value of 5% as an illustrative example.

In order to emphasize the impact of BR factors in the experiment and enhance the robustness of the model, the control group data was configured with a BR variable of 1 for all locations. As for the experimental group, 5% of the data was randomly selected to introduce noise, resulting in a BR variable of 0.75 for all places. Furthermore, the weight parameter λ for the iteration of information sharing experience was set at 10%.

To ensure the model's validity, this study employed a combination of whole-chain observations and step-by-step observations to compare the model's predicted results with the actual values. The accuracy of location choices for each step in the travel chain was observed and compared. For the end of the chain and travel time, the entire chain was observed to calculate the error for each step based on the actual chain.

To avoid potential biases in the simulation, different characteristic models were trained using the same batch of experimental data. The models were distinguished by modifying specific parameters while keeping others consistent, which treats the Indifference Zone portion for traffic zones, population, and distance as identical. However, it considers the departure time of different trips, the expected end time of today's trip, and the Indifference Zone portion of the travel cost at the current location as distinct. The total number of iterations for the model was controlled within the range of 400-450 to ensure stability and robustness of the resulting data. The error rate, expressed as the MAPE (Mean Absolute Percentage Error) value, was highest in the last 30 iterations.

C. MODEL ESTIMATION RESULTS

The constructed model was applied to dynamically simulate within-day travel location decision selection in 5 cities. The convergence process of the model is depicted in Fig. 9, and the prediction results are summarized in Table 2. The findings demonstrate that the LSTM model incorporating STBR exhibits a faster convergence rate and lower prediction error, as indicated in Fig. 9.

Regarding prediction accuracy, Table 2 reveals that the SBR-LSTM model, offers limited improvements compared to the PR-LSTM model. The reduction in prediction error is 28.97%, 7.44%, 8.65%, 8.89%, and 4.35% for Beijing, Shanghai, Wuhan, Shenzhen, and Hangzhou, respectively. On the other hand, the STBR-LSTM model yields the greatest improvement in prediction accuracy. The error reduction for the respective cities is 31.65%, 33.27%, 11.87%, 17.42%, and 7.30%. Overall, the STBR-LSTM model achieves a prediction accuracy of approximately 80%, which is about 10% higher than the SBR-LSTM model and more than 40% higher than the PR-LSTM model.

TABLE 2. The influence of bounded rationality in different cities.

City	Number of alternative sites	MAPE(%)			Error reduction (%)
		PR-LSTM	SBR-LSTM	STBR-LSTM	
Beijing	11	48.29	19.32	16.64	31.65
Shanghai	13	46.68	39.24	13.41	33.27
Wuhan	10	38.22	29.57	26.35	11.87
Hangzhou	10	62.27	53.38	44.85	17.42
Shenzhen	8	12.71	8.36	5.41	7.30
Mean	10.4	41.63	29.98	21.33	20.30

Through the comparison of simulation results in cities of varying sizes and populations, it is evident that the impact of BR becomes more pronounced as city size increases. Comparing the STBR-LSTM model with the SBR-LSTM model and the PR-LSTM model, notable improvements in prediction accuracy can be observed, particularly in megacities such as Beijing (48.29% to 16.64%) and Shanghai (46.68% to 13.41%), where the forecast error rates were reduced by more than 30%. Major cities like Wuhan (38.22% to 26.35%) and Hangzhou (62.27% to 44.85%) also experienced an increase in prediction accuracy by 10% to 20%. In the case of Shenzhen, where the number of sites is relatively small, the LSTM model incorporating STBR achieved a prediction error MAPE value of 8.36%, with a prediction accuracy of 91.64%, which is 7.30% higher compared to the model without considering STBR.

Analyzing the relationship between city size and prediction results, it becomes evident that the influence of STBR is widespread in the travel patterns of large cities. As cities expand in size, population, and the number of alternative locations, the impact of STBR on travelers' location choices becomes more prominent. Therefore, it is crucial to consider the influence of BR in complex travel systems, as the complexity of the system intensifies with urban growth.

To further validate the effectiveness and applicability of the method, simulations were conducted to analyze location decision selection behaviors based on travel time, travel steps, and travel characteristics. The results of these simulations are summarized in Table 3.

Table 3 reveals the significant improvement in prediction accuracy when considering STBR for both peak and off-peak

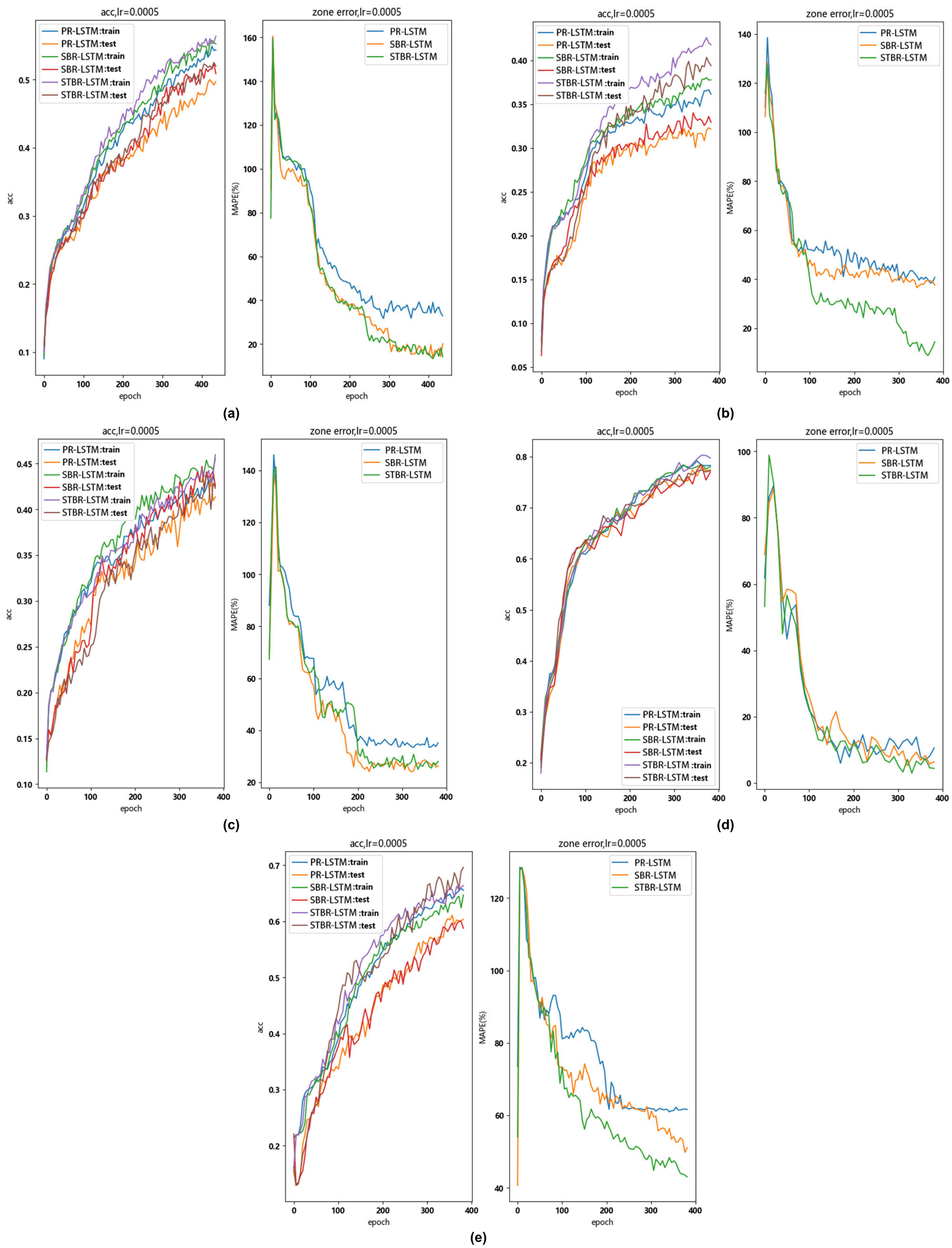

FIGURE 9. **LSTM prediction result (micro-Acc, macro-MAPE). (a) Beijing. (b) Shanghai. (c) Wuhan. (d) Shenzhen. (e) Hangzhou.**

travel scenarios. Specifically, the improvement effect for off-peak travel (27.45%) is more pronounced compared to peak travel (16.56%). This difference can be attributed to the fact that during peak travel, despite heightened awareness of temporal cost and a congested road network, travelers often have limited flexibility in choosing their locations,

TABLE 3. Simulation results of dynamic decision selection of travel location.

Scenario	Feature	MAPE(%)			Error reduction (%)
		PR-LSTM	SBR-LSTM	STBR-LSTM	
Travel time	Peak	77.98	78.06	61.42	16.56
	Flat peak	53.10	42.68	25.65	27.45
Number of activity points	Simple chain	58.58	57.98	56.38	2.20
	Complex chain	60.74	52.66	46.89	13.85
Importance of travel	Main step	54.16	49.88	47.87	6.29
	Other step	50.44	41.79	27.56	22.88

resulting in a less pronounced influence of BR on decision-making. Conversely, during off-peak travel, which encompasses periods with less traffic congestion, the influence of both spatial and temporal BR becomes more prominent, as travelers have greater freedom to optimize their location choices and reduce travel temporal costs. This observation validates the model's ability to capture the interplay between spatial and temporal factors in travel decision-making across different scenarios.

Upon comparing simple chains ($\leq$3 steps) and complex chains ($>$3 steps), it becomes evident that BR is better suited for location prediction in multi-point within-day travel and path planning involving a series of places, as opposed to simple two-point chains such as home-to-work commutes. The inclusion of BR has minimal impact on the prediction of simple chains (2.20% improvement). However, it significantly enhances the prediction accuracy of complex chains (13.85% improvement). This disparity can be attributed to the ability of BR to effectively capture the characteristics of paths comprising multiple locations and accurately calculate the Indifference Zone of utility between these locations. Conversely, for two-point travel scenarios, the introduction of BR may introduce a certain degree of instability in the predictions. In conclusion, considering the influence of STBR is essential in multi-point travel scenarios.

By calculating the proportion of step time to the total travel time within a day, it can be distinguished between the main step ($\geq$0.3) and other steps ($<$0.3). A larger proportion indicates a higher level of importance for that particular step. Based on the experimental findings, BR has a stronger impact on the prediction of other steps (22.88% improvement), suggesting that when each step of the day carries a similar weight, travelers' location choices are more influenced by BR. However, when there is a clearly dominant step in terms of importance, BR imposes constraints on the prediction of that step (6.29% improvement), as important locations tend to be less affected by minor variations in utility. Consequently, it can be inferred that the prediction performance of the main step is more pronounced, and a unilateral BR model struggles to ensure the stability of prediction results.

VI. DISCUSSION AND CONCLUSION

This study delves into the dynamic influence of spatial-temporal bounded rationality (STBR) on decision-making in the travel process. It considers the interplay of spatial and temporal factors in location choices, where the utility of alternative locations is evaluated against individual Indifference Zones in space, and the perception of remaining time is determined through information sharing and temporal cost perception. Two stages of bounded rationality (BR) behavior in travel location decision-making are proposed: 1) Travel utility is influenced by both spatial benefit and temporal cost, with dynamic and non-completely rational perceptions of benefit and cost. 2) After obtaining location priorities based on utility, travelers perceive travel time and expected remaining time, assess whether a trip is feasible, and explore alternative locations.

By employing a deep learning model, it is incorporated the Indifference Zone into the random utility component of multiple location choices, leading to the development of a within-day STBR-LSTM model that accounts for both spatial benefit and temporal cost. The interplay between individual BR decision-making and system network conditions is examined using in 5 cities' travel network. Through an exploration of BR impact on city size, peak and flat peak travel, simple and complex chains, and main and other steps, the following conclusions emerge from the numerical results:

(1) Location choices are influenced by both spatial and temporal factors. BR influence on space is characterized by "benefit dependence," as travelers prefer familiar places with lower randomness. BR influence on time is manifested in differentiated perception, with travelers' perception of temporal cost and remaining time being influenced by all travelers in the roadway network.

(2) The Indifference Zone and information sharing play crucial roles. A higher Indifference Zone threshold intensifies travelers' dependence on low-randomness places, making them less inclined to explore unknown locations. Information sharing complements cognition by smoothing perceived changes, with time proximity increasing the weight of shared information, thereby enhancing the efficiency of transforming system information into individual travel attributes.

(3) Compared to the control model (MAPE Mean 41.63%), the proposed model incorporating STBR (MAPE Mean 29.98%) exhibits significant advantages over the spatial-only model (MAPE Mean 21.33%) across all cities. The results of the STBR model demonstrate varying improvements in cities of different sizes (Beijing 31.65%, Shanghai 33.27%, Wuhan 11.87%, Hangzhou 17.42%, Shenzhen 7.30%), during peak (16.56%) or flat peak (27.45%) travel, simple chains (2.20%) or complex chains (13.85%), and main steps (6.29%) or other steps (22.88%). The influence of BR permeates travel behavior, with a significant increase in travelers' perception of BR as the number of alternative locations grows, road congestion worsens, location compositions become more intricate, and within-day travel gains more stability.

Obtaining convergence in the optimization of the travel system across the 5 cities requires aggregating travel analysis zones, aligning with previous research findings [41], [47]. This suggests that individual-level convergence of travel prediction optimization is challenging. Imperfect expression of BR information may contribute to this difficulty. Although the proposed model includes components and parameters that are not directly derivable, resulting in challenges in obtaining theoretical performance and behavioral insights, numerical examples and extensive sensitivity analyses demonstrate consistent and stable model outputs, even in the presence of noisy data interference and varying parameter selections.

Findings of this work will be of interest to network modelers aiming to predict and quantify the network effect of internal changes. This provides insights for urban functional zoning planning and traffic demand management, especially with the emerging technologies, such as adaptive traffic controls, and real-time information dissemination.

For future research, the potential enhancements could focus on the following directions: (1) Taking into account the heterogeneous vehicle schedule, fleet size and vehicle type are needed to optimize. (2) While considering the dynamics of the threshold of BR, the more perfect expression of BR information would lead more realistic prediction results. (3) Use the spatial-temporal model to predict stay time, and further coupling location and time into a complete route.

REFERENCES

[1] R. Kitamura, "Incorporating trip chaining into analysis of destination choice," *Transp. Res. B, Methodol.*, vol. 18, no. 1, pp. 67–81, Feb. 1984, doi: 10.1016/0191-2615(84)90007-9.

[2] A. Huang and D. Levinson, "Axis of travel: Modeling non-work destination choice with GPS data," *Transp. Res. C, Emerg. Technol.*, vol. 58, pp. 208–223, Sep. 2015, doi: 10.1016/j.trc.2015.03.022.

[3] K. J. Clifton, P. A. Singleton, C. D. Muhs, and R. J. Schneider, "Development of destination choice models for pedestrian travel," *Transp. Res. A, Policy Pract.*, vol. 94, pp. 255–265, Dec. 2016, doi: 10.1016/j.tra.2016.09.017.

[4] G. A. Malavenda, G. Musolino, C. Rindone, and A. Vitetta, "Residential location, mobility, and travel time: A pilot study in a small-size Italian metropolitan area," *J. Adv. Transp.*, vol. 2020, Aug. 2020, Art. no. 8827466, doi: 10.1155/2020/8827466.

[5] F. Hatami, Md. M. Rahman, B. Nikpparvar, and J.-C. Thill, "Non-linear associations between the urban built environment and commuting modal split: A random forest approach and SHAP evaluation," *IEEE Access*, vol. 11, pp. 12649–12662, 2023, doi: 10.1109/ACCESS.2023.3241627.

[6] D. T. Phan, H. L. Vu, and E. J. Miller, "A new approach to improve destination choice by ranking personal preferences," *Transp. Res. C, Emerg. Technol.*, vol. 143, Oct. 2022, Art. no. 103817, doi: 10.1016/j.trc.2022.103817.

[7] Y.-S. Lin, A. R. Srinivasan, M. Leonetti, J. Billington, and G. Markkula, "A utility maximization model of pedestrian and driver interactions," *IEEE Access*, vol. 10, pp. 118888–118899, 2022, doi: 10.1109/ACCESS.2022.3213363.

[8] A. Vega and A. Reynolds-Feighan, "A methodological framework for the study of residential location and travel-to-work mode choice under central and suburban employment destination patterns," *Transp. Res. A, Policy Pract.*, vol. 43, no. 4, pp. 401–419, May 2009, doi: 10.1016/j.tra.2008.11.011.

[9] S. Bekhor and J. N. Prashker, "GEV-based destination choice models that account for unobserved similarities among alternatives," *Transp. Res. B, Methodol.*, vol. 42, no. 3, pp. 243–262, Mar. 2008, doi: 10.1016/j.trb.2007.08.003.

[10] D. McFadden, "Modeling the choice of residential location," *Transp. Res. Rec.*, 1977.

[11] C. R. Bhat and J. Guo, "A mixed spatially correlated logit model: Formulation and application to residential choice modeling," *Transp. Res. B, Methodol.*, vol. 38, no. 2, pp. 147–168, Feb. 2004, doi: 10.1016/S0191-2615(03)00005-5.

[12] M. Li, F. Chen, and Q. Lin, "Random regret minimization model for variable destination-oriented path planning," *IEEE Access*, vol. 8, pp. 163646–163659, 2020, doi: 10.1109/ACCESS.2020.3021524.

[13] N. Golshani, R. Shabanpour, A. K. Mohammadian, J. Auld, and H. Ley, "Analysis of evacuation destination and departure time choices for no-notice emergency events," *Transportmetrica A, Transp. Sci.*, vol. 15, no. 2, pp. 896–914, Nov. 2019, doi: 10.1080/23249935.2018.1546778.

[14] T.-Y. Hu and H. S. Mahmassani, "Day-to-day evolution of network flows under real-time information and reactive signal control," *Transp. Res. C, Emerg. Technol.*, vol. 5, no. 1, pp. 51–69, Feb. 1997, doi: 10.1016/S0968-090X(96)00026-5.

[15] J. Y. T. Wang and M. Ehrgott, "Modelling route choice behaviour in a tolled road network with a time surplus maximisation bi-objective user equilibrium model," *Transp. Res. B, Methodol.*, vol. 57, pp. 342–360, Nov. 2013, doi: 10.1016/j.trb.2013.05.011.

[16] C. J. Khisty and T. Arslan, "Possibilities of steering the transportation planning process in the face of bounded rationality and unbounded uncertainty," *Transp. Res. C, Emerg. Technol.*, vol. 13, no. 2, pp. 77–92, Apr. 2005, doi: 10.1016/j.trc.2005.04.003.

[17] T. Lotan, "Effects of familiarity on route choice behavior in the presence of information," *Transp. Res. C, Emerg. Technol.*, vol. 5, nos. 3–4, pp. 225–243, Aug. 1997, doi: 10.1016/S0968-090X(96)00028-9.

[18] R. Michael, "Network knowledge and route choice," Ph.D. thesis, Dept. Civil Environ. Eng., Massachusetts Inst. Technol., Cambridge, MA, USA, 2002. [Online]. Available: http://hdl.handle.net/1721.1/49797

[19] C. G. Prato and S. Bekhor, "Applying branch-and-bound technique to route choice set generation," *Transp. Res. Rec.*, vol. 1985, no. 1, pp. 19–28, 2006.

[20] Y. Yu, K. Han, and W. Ochieng, "Day-to-day dynamic traffic assignment with imperfect information, bounded rationality and information sharing," *Transp. Res. C, Emerg. Technol.*, vol. 114, pp. 59–83, May 2020, doi: 10.1016/j.trc.2020.02.004.

[21] X. Zhang and H. Guan, "A travel decision making model based on nested logit model considering bounded rationality," *IEEE Access*, vol. 8, pp. 152465–152473, 2020, doi: 10.1109/ACCESS.2020.3014618.

[22] H. S. Mahmassani and G.-L. Chang, "On boundedly rational user equilibrium in transportation systems," *Transp. Sci.*, vol. 21, no. 2, pp. 89–99, May 1987, doi: 10.1287/trsc.21.2.89.

[23] B. Liu, G. Zhu, X. Li, and R. Sun, "Vulnerability assessment of the urban rail transit network based on travel behavior analysis," *IEEE Access*, vol. 9, pp. 1407–1419, 2021, doi: 10.1109/ACCESS.2020.3047159.

[24] R.-Y. Guo, H. Yang, and H.-J. Huang, "Are we really solving the dynamic traffic equilibrium problem with a departure time choice?" *Transp. Sci.*, vol. 52, no. 3, pp. 603–620, Jun. 2018, doi: 10.1287/trsc.2017.0764.

[25] Y. Lou, Y. Yin, and S. Lawphongpanich, "Robust congestion pricing under boundedly rational user equilibrium," *Transp. Res. B, Methodol.*, vol. 44, no. 1, pp. 15–28, Jan. 2010, doi: 10.1016/j.trb.2009.06.004.

[26] M. Ridwan, "Fuzzy preference based traffic assignment problem," *Transp. Res. C, Emerg. Technol.*, vol. 12, nos. 3–4, pp. 209–233, Jun. 2004, doi: 10.1016/j.trc.2004.07.003.

[27] E. A. I. Bogers, F. Viti, and S. P. Hoogendoorn, "Joint modeling of advanced travel information service, habit, and learning impacts on route choice by laboratory simulator experiments," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1926, no. 1, pp. 189–197, Jan. 2005.

[28] Y. E. Ge and X. Zhou, "An alternative definition of dynamic user optimum on signalised road networks," *J. Adv. Transp.*, vol. 46, no. 3, pp. 236–253, Jul. 2012, doi: 10.1002/atr.207.

[29] H. Wang, H. Guan, H. Qin, W. Li, and J. Zhu, "A slack departure strategy for demand responsive transit based on bounded rationality," *J. Adv. Transp.*, vol. 2022, May 2022, Art. no. 9693949, doi: 10.1155/2022/9693949.

[30] K. Han, W. Y. Szeto, and T. L. Friesz, "Formulation, existence, and computation of boundedly rational dynamic user equilibrium with fixed or endogenous user tolerance," *Transp. Res. B, Methodol.*, vol. 79, pp. 16–49, Sep. 2015, doi: 10.1016/j.trb.2015.05.002.

[31] H. Yang and H.-J. Huang, "The multi-class, multi-criteria traffic network equilibrium and systems optimum problem," *Transp. Res. B, Methodol.*, vol. 38, no. 1, pp. 1–15, Jan. 2004, doi: 10.1016/S0191-2615(02)00074-7.

[32] H. Ye and H. Yang, "Rational behavior adjustment process with boundedly rational user equilibrium," *Transp. Sci.*, vol. 51, no. 3, pp. 968–980, Aug. 2017, doi: 10.1287/trsc.2016.0715.

[33] H. K. Lo and W. Y. Szeto, "A cell-based variational inequality formulation of the dynamic user optimal assignment problem," *Transp. Res. B, Methodol.*, vol. 36, no. 5, pp. 421–443, Jun. 2002, doi: 10.1016/S0191-2615(01)00011-X.

[34] T. Iryo, "Day-to-day dynamical model incorporating an explicit description of individuals' information collection behaviour," *Transp. Res. B, Methodol.*, vol. 92, pp. 88–103, Oct. 2016, doi: 10.1016/j.trb.2016.01.009.

[35] L. Li, S. He, J. Zhang, and B. Ran, "Short-term highway traffic flow prediction based on a hybrid strategy considering temporal–spatial information," *J. Adv. Transp.*, vol. 50, no. 8, pp. 2029–2040, Dec. 2016, doi: 10.1002/atr.1443.

[36] N. Awan, A. Ali, F. Khan, M. Zakarya, R. Alturki, M. Kundi, M. D. Alshehri, and M. Haleem, "Modeling dynamic spatio-temporal correlations for urban traffic flows prediction," *IEEE Access*, vol. 9, pp. 26502–26511, 2021, doi: 10.1109/ACCESS.2021.3056926.

[37] L. Han, S. Ukkusuri, and K. Doan, "Complementarity formulations for the cell transmission model based dynamic user equilibrium with departure time choice, elastic demand and user heterogeneity," *Transp. Res. B, Methodol.*, vol. 45, no. 10, pp. 1749–1767, Dec. 2011, doi: 10.1016/j.trb.2011.07.007.

[38] W. Y. Szeto and H. K. Lo, "A cell-based simultaneous route and departure time choice model with elastic demand," *Transp. Res. B, Methodol.*, vol. 38, no. 7, pp. 593–612, Aug. 2004, doi: 10.1016/j.trb.2003.05.001.

[39] X. Huang, Y. Ye, X. Yang, and L. Xiong, "Multistep coupled graph convolution with temporal-attention for traffic flow prediction," *IEEE Access*, vol. 10, pp. 48179–48192, 2022, doi: 10.1109/ACCESS.2022.3172341.

[40] Y. Xiao and H. K. Lo, "Day-to-day departure time modeling under social network influence," *Transp. Res. B, Methodol.*, vol. 92, pp. 54–72, Oct. 2016, doi: 10.1016/j.trb.2016.05.006.

[41] F. Wei, N. Jia, and S. Ma, "Day-to-day traffic dynamics considering social interaction: From individual route choice behavior to a network flow model," *Transp. Res. B, Methodol.*, vol. 94, pp. 335–354, Dec. 2016, doi: 10.1016/j.trb.2016.10.002.

[42] C. Zhang, T.-L. Liu, H.-J. Huang, and J. Chen, "A cumulative prospect theory approach to commuters' day-to-day route-choice modeling with friends' travel information," *Transp. Res. C, Emerg. Technol.*, vol. 86, pp. 527–548, Jan. 2018, doi: 10.1016/j.trc.2017.12.005.

[43] K. Nurul Habib, "A comprehensive utility-based system of activity-travel scheduling options modelling (CUSTOM) for worker's daily activity scheduling processes," *Transportmetrica A, Transp. Sci.*, vol. 14, no. 4, pp. 292–315, Apr. 2018, doi: 10.1080/23249935.2017.1385656.

[44] M. J. Roorda, E. J. Miller, and K. M. N. Habib, "Validation of TASHA: A 24-h activity scheduling microsimulation model," *Transp. Res. A, Policy Pract.*, vol. 42, no. 2, pp. 360–375, Feb. 2008, doi: 10.1016/j.tra.2007.10.004.

[45] R. Arnott, A. De Palma, and R. Lindsey, "Departure time and route choice for the morning commute," *Transp. Res. B, Methodol.*, vol. 24, no. 3, pp. 209–228, Jun. 1990, doi: 10.1016/0191-2615(90)90018-T.

[46] R.-Y. Guo, H. Yang, H.-J. Huang, and X. Li, "Day-to-day departure time choice under bounded rationality in the bottleneck model," *Transp. Res. B, Methodol.*, vol. 117, pp. 832–849, Nov. 2018, doi: 10.1016/j.trb.2017.08.016.

[47] W. Y. Szeto and H. K. Lo, "Dynamic traffic assignment: Properties and extensions," *Transportmetrica*, vol. 2, no. 1, pp. 31–52, Jan. 2006, doi: 10.1080/18128600608685654.

CHUNJIAO DONG received the Ph.D. degree in transportation planning and management from Beijing Jiaotong University, Beijing, China, in 2011. She was a Postdoctoral Research Associate with the Center for Transportation Research, The University of Tennessee, Knoxville, TN, USA, from 2011 to 2014, and a Research Assistant Professor, from 2014 to 2019. She is currently a Professor with Beijing Jiaotong University. Her research interests include transportation planning and management, traffic control and safety, and intelligent transportation theory.

JIAYU BAO was born in 1998. He received the B.S. degree from the School of Transportation and Logistics Engineering, Wuhan University of Technology, Wuhan, China, in 2017. He is currently pursuing the M.S. degree in transportation planning and management with Beijing Jiaotong University, Beijing, China. His research interests include travel behavior analysis, and traffic control and safety.

JING WANG was born in 1995. She received the M.S. degree in transportation planning and management from Beijing Jiaotong University, Beijing, China, in 2020, where she is currently pursuing the Ph.D. degree in transportation planning and management. Her research interests include public transportation, human mobility, and data mining and visualization.

JUNYUE WANG was born in 1999. She received the B.S. degree in engineering from the School of Traffic and Transportation, Beijing Jiaotong University, Beijing, China, in 2017. She is currently pursuing the Ph.D. degree in transportation planning and management with Beijing Jiaotong University. Her research interests include travel behavior and human mobility.