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Research Article

A Travel Demand Response Model in MaaS Based on Spatiotemporal Preference Clustering

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To respond to travel demand in the MaaS system, improve transport efficiency, and optimize the framework of MaaS, we propose a travel demand response model based on a spatiotemporal preference clustering algorithm that considers the impact of travel preferences and features of the MaaS system to improve travel demand response and achieve full coverage of travel demands. Specifically, in the MaaS system, the time preference hierarchical clustering algorithm is optimized with travel preference as the perception factor and preference priority order as the iteration index. Then, we cluster the departure and arrival times of reservation demand points and iteratively analyze the discrete points to obtain the set of reservation demand points with convergent time dimensions under similar preferences. Then, the spatial preference DBSCAN clustering algorithm is improved with travel preference and preference priority order as the iteration indices, and spatial clustering of the time-dense points are updated by the silhouette coefficient to obtain reservation demand points with similar spatiotemporal preference and respond to the demands. Meanwhile, traffic resources are coordinated by the MaaS system and the flexible means of transport are deployed to spatiotemporal discrete points to achieve full coverage of travel demand. Simulation shows that when the neighborhood range is 0.5 km and the least number of reservation demand sites is 3, our spatiotemporal model achieves a response rate of reservation demand points at 95%, and a demand coverage rate of 100%, which is 15% and 6.7% higher than the hierarchical clustering model and the DBSCAN clustering model, respectively. The demand response rate is also improved compared to the spatiotemporal clustering model in the customized bus model. The model and algorithm have some applicability and can be applied to areas with fixed, semifixed and flexible route transport, thereby considerably improving the travel demand response efficiency and transport service quality.

1. Introduction

Mobility as a service (MaaS), a type of integrated service to meet mobility demands, can solve the problem of demand-supply imbalance in traditional traffic services and has thus become a hot research topic in the domain of travel demand response (TDR). It constructs a traffic and travel mechanism based on travel preferences, which is of great importance to build a demand-specific traffic service mode.

The notion of MaaS was first proposed at the 2014 Intelligent Transport System World Congress [1]: MaaS is a type of service that meets users' travel needs through a transportation provider and integrates different means of transport to provide customized travel packages to passengers. Based on the travel demand of passengers, MaaS integrates different means of transport into a service system and builds an information service platform that allows the users to book, plan, pay, and comment on the services to optimize the allocation of resources and meets users' needs for mobility to the greatest extent [2]. The MaaS system provides integrated services [3], achieves sharing of travel information [4], provides a user-friendly experience, and follows the principle of low-carbon development [5], which enables a shift from personally owned modes of transportation to the mobility provided as a service for consumption [6]. Research on MaaS is still in its infancy.

Jitrapirom et al. [7] found through surveys that transportation services customized by MaaS can improve traveling efficiency and respond timely to travel demand, which draws more research attention to improve the MaaS system and apply it to urban transportation. First, Streeting et al. [8] explored the key attributes of MaaS and described it in terms of user experience and technical workflow. Djavadian et al. [9] specified the key technical challenges facing the MaaS system: transportation sharing, integrated payment, and customized services, which provides constructive suggestions for improving the MaaS system. This literature provides ideas for the construction of MaaS systems within this study. Kamargianni et al. [10] summarized the four necessary aspects of the MaaS system: policy, business, technology, and user. Konig et al. [11] focused on the business aspect of MaaS and indicated that the operators engage the government, private enterprise, transportation service provider, and technical service provider. Audouin et al. [12] pointed out that long-term and comprehensive system design and mature policy support are key contributors to the wellbeing of the MaaS industry. This literature shows that MaaS systems need to focus on the coordination of multiple transportation modes and the needs of travelers. The MaaS system built in this study takes the needs of travelers as an important object of study. To sum up, existing works on MaaS focus on framework design and structural analysis, but studies on dynamic response to travel demands are rare and short of quantitative analysis. Therefore, a travel demand response model in the MaaS system is studied here to solve the problems of response to reservation points and mobility demand coverage, which provides theoretical and technical support for the development of the MaaS system.

The quantitative study of demand-responsive transportation is currently one of the hot issues of interest to experts and scholars. First, Brake et al. [13] analyzed the contributing factors to travel demand response under the demand-responsive transport (DRT) mode and corresponding optimization strategies. However, it is also pointed out that there are problems to be solved in building a reasonable reservation system and an appropriate service system. Errico et al. [14] constructed a travel demand response (TDR) framework based on the flexible transit service (FTS) and pointed out that it has limitations of the service. All these literature suggest that demand-responsive transportation systems should enhance serviceability and that the MaaS system model constructed in this paper should improve single service applications and enhance travel demand response rates. Qiu et al. [15] put forward a dynamic site strategy that optimizes the quality of FTS systems. It also points to information such as demand distribution and external environment as key factors influencing the strategy. Xue et al. [16] studied the response mechanism of customized bus systems based on the spatiotemporal dimensions and achieved strategies for parameter optimization. All these studies by experts and scholars show that the spatiotemporal distribution characteristics are the basis and focus of research for intracity traffic demand. The demand response algorithm proposed in this study should be constructed in conjunction with the spatiotemporal distribution of travel demand. Case studies on Gothenburg [17], London [18], and Sydney [19] show that travel preference is a key factor in the MaaS system. Travel preference, if analyzed in depth and is fully utilized, can improve the system's appeal to travelers and increase the efficiency of traffic resources. Therefore, the algorithm designed for this study should also analyze the traveler's preference choice as an important factor.

To sum up, based on the spatiotemporal distribution of travel demand and features of travel preferences, a spatiotemporal preference clustering algorithm is designed and a travel demand response model in the MaaS is proposed to coordinate traffic resources. The proposed method is expected to improve the MaaS framework in China and quantitative analysis of travel demand response. Solving the problem of traffic demand response under the MaaS system increases the efficiency of travel demand response and improves transport service quality and the system's appeal to passengers. It is an important study to help the practical application of MaaS and its promotion in various places.

2. Model Construction

2.1. Travel Demand Response (TDR) Model in the MaaS System. In the MaaS system, three modes of transport are defined: fixed route transport, semifixed route transport, and flexible route transport, and a travel demand response (TDR) model is constructed accordingly, as shown in Figure 1.

As Figure 1 shows, reservation demand points represent the spatiotemporal data points of travelers' transportation demand. Travel preference indicates the traveler's preference or order of preference for various modes of transportation. Fixed route transport means public transportation with fixed routes, semifixed route transport means traffic with partially variable operating routes, and flexible route transport means that the operation route and service area can be changed according to the demand [20].

Based on the traffic situation in our country and the description of each parameter mentioned above, the parameters of the MaaS model in this study are determined as given below:

(1) In this model, the fixed route transport is a bus, the semifixed route transport is a customized bus, and the flexible route transport refers to service provided by cars hailed online

(2) The bus and customized bus in the model have a carrying capacity of eight, and the car hailed online has a carrying capacity of three

(3) To ensure the service quality, route-changeable transport services are not provided by any transport means in the model

(4) Travelers upload travel needs to the online platform, which generates reservation demand points.

2.2. Spatiotemporal Preference Clustering Algorithm. Considering the impact of travel preference, a spatiotemporal preference clustering algorithm is constructed to achieve clustering and coverage of reservation demand

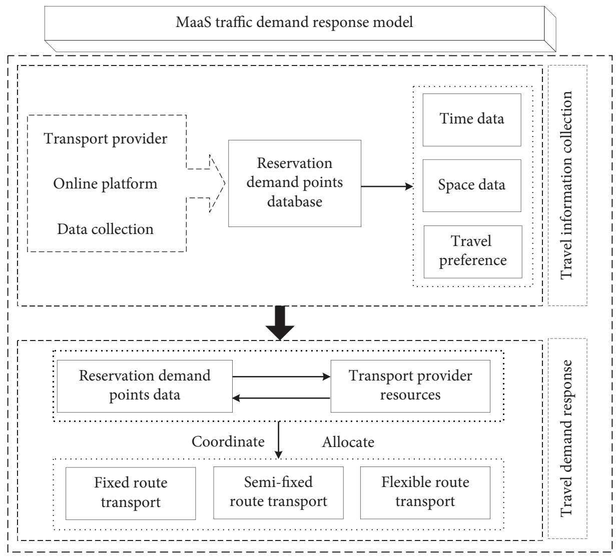

Figure 1: MaaS travel demand response model.

points in the MaaS system. The proposed model clusters the transient spatiotemporal distribution of travel demands and allocates traffic resources. According to the concepts related to general travel costs [21], travel time and accessibility can provide potential benefits to the traveler compared to spatial distance (within walking distance). Spatiotemporal dimensions are simultaneously calibrated to meet the temporal, and spatial data of the reservation demand points are clustered at the same time. The order of "temporal dimension first and then spatial dimension" can reduce the clustering difficulty and improve the clustering response rate compared with the spatiotemporal calibration simultaneously. Therefore, this model first collects the demand point data of the web platform at a certain moment. Then, the demand points are clustered for time preference to obtain dense and discrete points. Second, it performs location preference clustering on the time-preference dense points to obtain spatiotemporal dense points and discrete points. Last, according to the MaaS-coordinated traffic means, the discrete points are re-clustered to meet more travel demands, as shown in Figure 2 and Figure 3.

2.3. Spatiotemporal Preference Clustering Steps. The spatiotemporal preference clustering algorithm is constructed on the basis of MaaS combined with travel preferences, which is shown in the following steps:

(1) Building a database of reservation demand points: collecting reservation demand point data (travel time and space data and travel preference priority order) on the web platform and building a database as the basis for demand response;

(2) Hierarchical clustering of departure time preference: first, the reservation demand points are divided according to travel preferences, and the departure times are clustered hierarchically within each sample set. Second, the discrete points that appear after clustering each sample set is divided again according to the order of travel preference priority and the sample set is updated. Then, the abovementioned operation is repeated for the updated sample set until the travel preference order of the discrete points is the lowest. Finally, these discrete points are divided into flexible traffic and clustered again to output dense and discrete sets of the same preference. The MaaS model proposed in this study contains fixed, semifixed, and flexible route transport modes, and the discrete points generated by hierarchical clustering are iterated and clustered again according to the order of travel mode preferences, so as to enhance the clustering effect. The reservation demand points that are still discrete after iterative analysis can be served by flexible route transport to meet their travel needs.

(3) Hierarchical clustering of arrival time preferences: first, refer to step 2 to perform hierarchical clustering of arrival time data of reservation demand points and output the dense set and discrete set of the same preferences. Second, the reservation demand points with intersection within the departure time-intensive set and arrival time-intensive set are reserved. It is used as the database for spatial preference clustering, while the rest of the reservation demand points is classified to flexible transportation. The MaaS system's flexible route transport mode (net car) has a freer service radius and service routes and therefore can take on the demand for travel from discrete points.

(4) Departure location preference DBSCAN clustering: first, based on the time-dimensional data set derived from step 3, the DBSCAN clustering algorithm is used to determine the dense and discrete points within the same preference set. Second, since the DBSCAN algorithm is less effective in clustering unevenly distributed data, the clustering parameters are optimized by calculating the contour coefficients

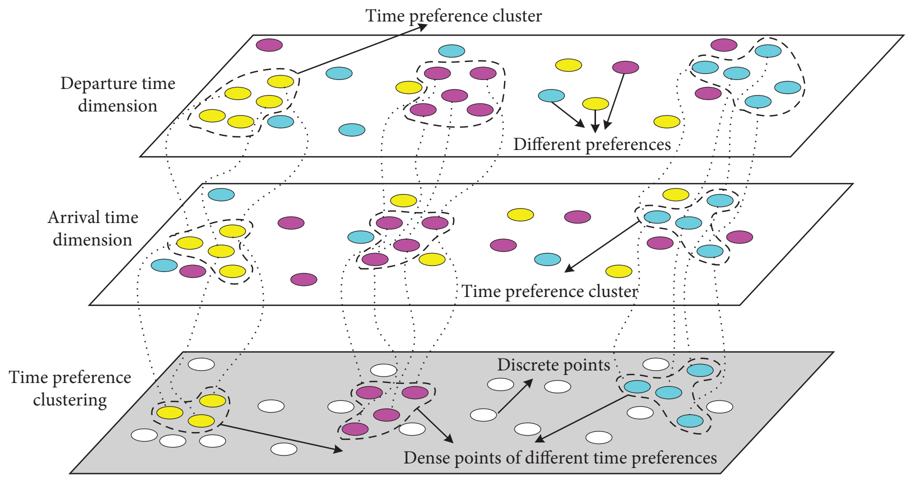

FIGURE 2: Time preference clustering of reservation demand points.

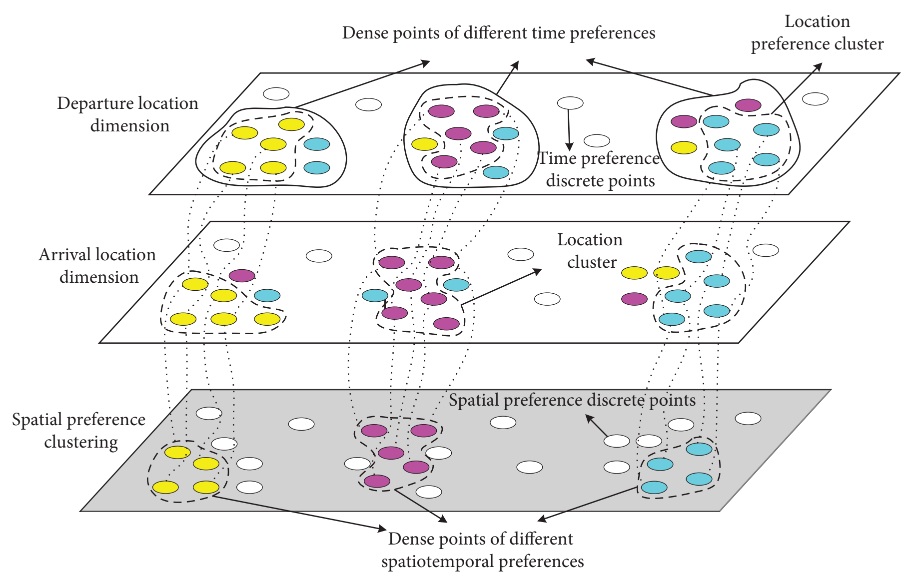

FIGURE 3: Spatiotemporal preference clustering of reservation demand points.

of the clustering results and using them as indicators. Finally, the clustering algorithm is executed again after updating the parameters and obtaining the dense and discrete sets of departure locations under the same preference.

(5) Arrival location preference DBSCAN clustering: first, DBSCAN clustering is performed on the arrival locations of the reservation demand points with reference to step 4, and the dense set and discrete set of arrival locations with the same preference are output. Second, reservation demand points with intersections within the dense set of departure locations and the dense set of arrival locations are retained, and the discrete points are classified into flexible route transport and clustered again to obtain the updated dense set and discrete set. Finally, the reservation demand points that are still discrete are assigned to flexible route transport for separate services.

The details and formulas for each step are shown in Sections 3 and 4.

3. Time Preference Hierarchical Clustering of Reservation Demand Points

3.1. Construction of a Reservation Demand Points Database. MaaS transport service providers need to collect data on reservation demand points from the online platform and construct a database: $Q = \{P, T, T', O, D, \Delta\}$, where Q is the demand points data, P is the set of reservation demand points, T is the set of departure time, T' is the set of arrival time, O is the set of departure locations, D is the set of arrival locations, and Δ is the travel preference priority level. Table 1 shows the database of reservation demand points.

In Table 1, $P = \{p_1, p_2 \ldots p_n\}$, where p_i is the i-th reservation demand point, $T = \{t_1, t_2 \ldots t_n\}$, and t_i is the departure time of p_i, $T' = \{t'_1, t'_2 \ldots t'_n\}$, and t'_i is the arrival time of p_i, $O = \{(x_1, y_1), (x_2, y_2) \ldots (x_n, y_n)\}$, where x_i and y_i are the

Table 1: Reservation demand points database.

P	T	T'	O	D	Δ
p_1	t_1	t'_1	(x_1, y_1)	(x'_1, y'_1)	$\delta_1(a,b,c)$
p_2	t_2	t'_2	(x_2, y_2)	(x'_2, y'_2)	$\delta_2(a,b,c)$
...	...	...	...	...	...
p_n	t_n	t'_n	(x_n, y_n)	(x'_n, y'_n)	$\delta_n(a,b,c)$

abscissa and ordinate of the departure site of p_i, $D = \{(x'_1, y'_1), (x'_2, y'_2)\ldots(x'_n, y'_n)\}$, where x'_i and y'_i are the abscissa and ordinate of the arrival point of p_i, respectively; $\Delta = \{\delta_1(a,b,c)\ldots\delta_n(a,b,c)\}$, where $\delta_i(a,b,c)$ are the priority order of travel preferences of p_i, and a, b, c represent the preferences for fixed route transport, semifixed route transport, and flexible route transport, respectively. The meaning of each symbol in Table 1 is detailed in the Table 2.

3.2. Hierarchical Clustering of Departure Time Preference. A temporal preference hierarchical clustering algorithm that considers the MaaS system features and passengers' preference priority order is constructed, as shown in Figure 4.

Follow the process shown in Figure 4 for time preference hierarchical clustering. The sample set is divided according to the priority order of reservation demand points, which is marked as N^{ij}. N^{ij} represents the reservation points set obtained through the set of reservation demand points with the i-th travel preference after the j-th iteration of departure time, where $i \in (a,b,c)$, and $j \in (1,2,3,4)$. Through hierarchical clustering of the departure time T of each reservation demand point within N^{ij}. This hierarchical clustering algorithm uses Average Linkage to calculate the class cluster distance [22] and obtains the more time-concentrated class clusters. Specifically, as shown in equations (1) and (2):

$$S_{R_{ij}} = \sqrt{\frac{\left(R_i - R_j\right)^2}{n_{R_i} + n_{R_j}}} = \sqrt{\frac{\sum\left(t_{R_i} - t_{R_j}\right)^2}{n_{R_i} + n_{R_j}}}, \quad (1)$$

$$\begin{cases} R_i, R_j \in M & S_{R_{ij}} \le \tau, n_{R_i} \ge \varphi, \\ R_i, R_j \in G & S_{R_{ij}} \le \tau, n_{R_i} < \varphi, \\ R_i, R_j \in G & S_{R_{ij}} \ge \tau, \end{cases} \quad (2)$$

where $S_{R_{ij}}$ is the distance between the i-th cluster and the j-th cluster calculated by the average linkage method, R_i and R_j represent the i-th and the j -th cluster that contain at least one reservation demand point; n_{R_i} and n_{R_j} are the number of points within the i-th and the j-th clusters, respectively; t_{R_i} and t_{R_j} are the departure time of reservation demand points within R_i and R_j; τ is the time span (min); M is the set of dense points with the same time preference; G is the set of discrete points of the same time preference; and φ is the minimum number of passengers. Its value is related to the authorized passenger capacity and full load ratio of the vehicle. While there are multiple transportation modes in MaaS, the average value is taken here as the minimum number of passengers, which is calculated as follows:

$$\varphi = \overline{\sum_i z_i \cdot \delta_i}, \quad (3)$$

where z_i is the passenger capacity of the i-th means of transport. δ_i is the expected full load rate of the i-th means of transport, since there are peak and flat peaks in travel time, the average value of 50% is taken to simplify the calculation. M and G of the same time preference are the alternative sets of arrival time preference hierarchical clusters. The meanings of the symbols within the algorithm and formulas are detailed in the Table 2.

3.3. Hierarchical Clustering of Arrival Time Preference. Hierarchical clustering is performed on arrival time preference and the obtained set is compared with the alternative sets. If there are intersections, the sample is incorporated into the set of dense points of different time preferences; if there are no intersections, the sample is incorporated into the set of discrete points on the temporal dimension.

(1) As per the descriptions in Section 3.2, hierarchical clustering of arrival time preference of reservation demand points is performed to obtain the sets $N^{ij\prime}$, M', and G'. $N^{ij\prime}$ is the set of reservation points obtained through the j-th iteration of the arrival time of points with the i-th travel preference, where $i \in (a,b,c)$, and $j \in (1,2,3,4)$; M' is the set of dense points of the same arrival time preference; G' is the set of discrete points of the same arrival time preference.

(2) The sets M' and G' are compared with the alternative sets M and G specified in Section 3.2. If there is an intersection, it is kept to the set of dense points, and if there is no intersection, it is divided into the set of discrete points, so as to obtain the result of time preference clustering. The specific discriminant method was obtained with reference to the literature [16] and is as shown in the following equations:

$$\begin{cases} p_i^m \notin S & M \cap M' \neq \varnothing, \\ p_i^m \in S & M \cap M' = \varnothing, \\ p_i^g \in S, \end{cases} \quad (4)$$

where S is the set of discrete points of time preference, p_i^m represents a reservation demand point that belongs to both M and M', and p_i^g represents a reservation demand point that belongs to both G and G'.

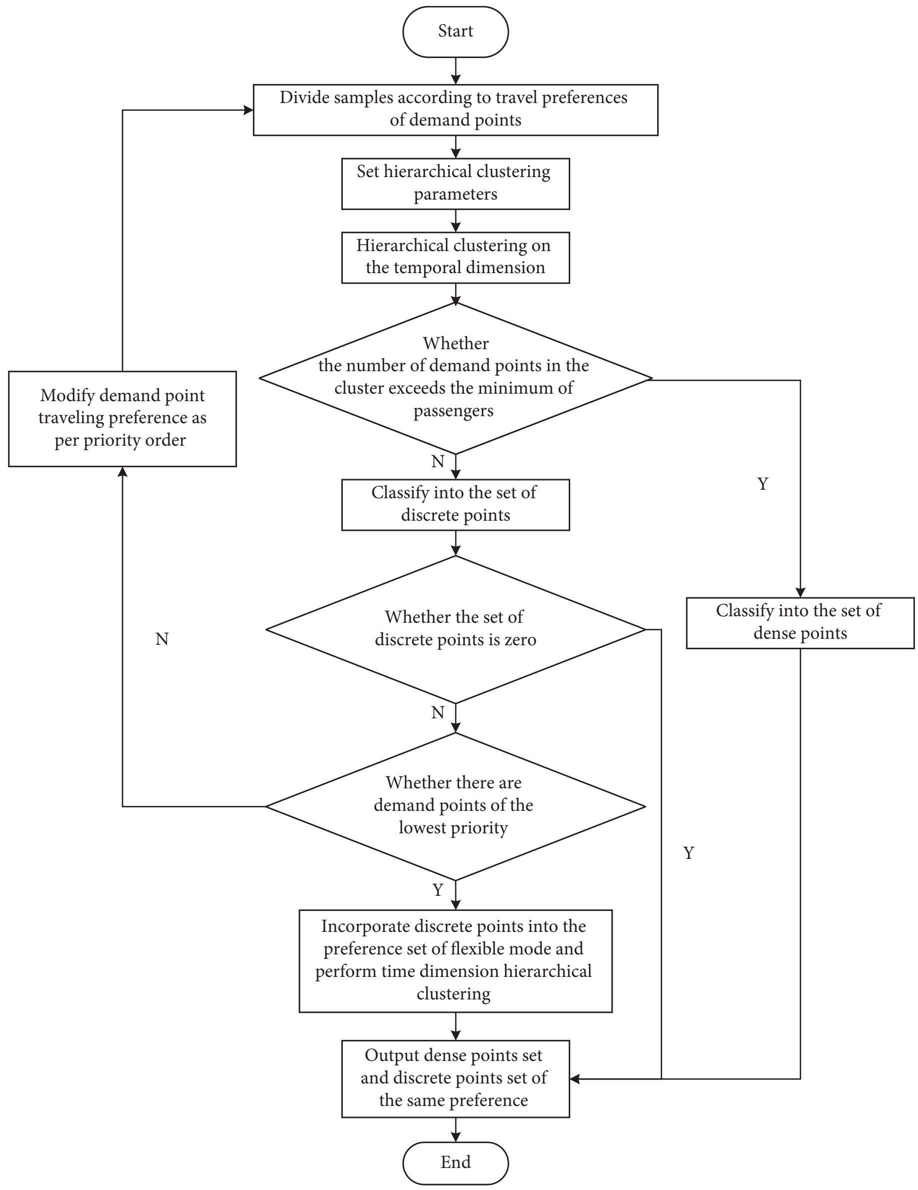

Figure 4: Workflow of the time preference hierarchical clustering algorithm.

All reservation demand points in S are assigned to the flexible route transport mode to achieve full coverage of demand. Other dense points are classified by preference into M^a, M^b, and M^c, which are sets of dense points with a temporal preference for fixed route transport, semifixed route transport, and flexible route transport, respectively. The meanings of the symbols within the algorithm and formulas are detailed in the Table 2.

4. Spatial Preference DBSCAN Clustering of Reservation Demand Points

4.1. Departure Location Preference DBSCAN Clustering. Spatial preference DBSCAN clustering is performed on the departure location data based on the dense points of time preference [23]. The DBSCAN algorithm is a density-based algorithm, and according to the traffic demand response theory, the improved parameters are defined as follows:

Definition 1. ε neighborhood of the reservation demand point p_i. The ε neighborhood of the reservation demand point $\forall p_i \in P$ is termed $\varepsilon(p_i)$, which is defined as follows: a set of all reservation points within a circle with p_i as the center and ε as the radius, it is summarized by definition as follows:

$$\varepsilon(p_i) = \left\{p_j \in P | \text{dist}\left(p_i, p_j\right) \leq \varepsilon\right\}, \quad (5)$$

where P is the set of reservation demand points within the samples, and $\text{dist}(p_i, p_j)$ is the distance between two points p_i and p_j.

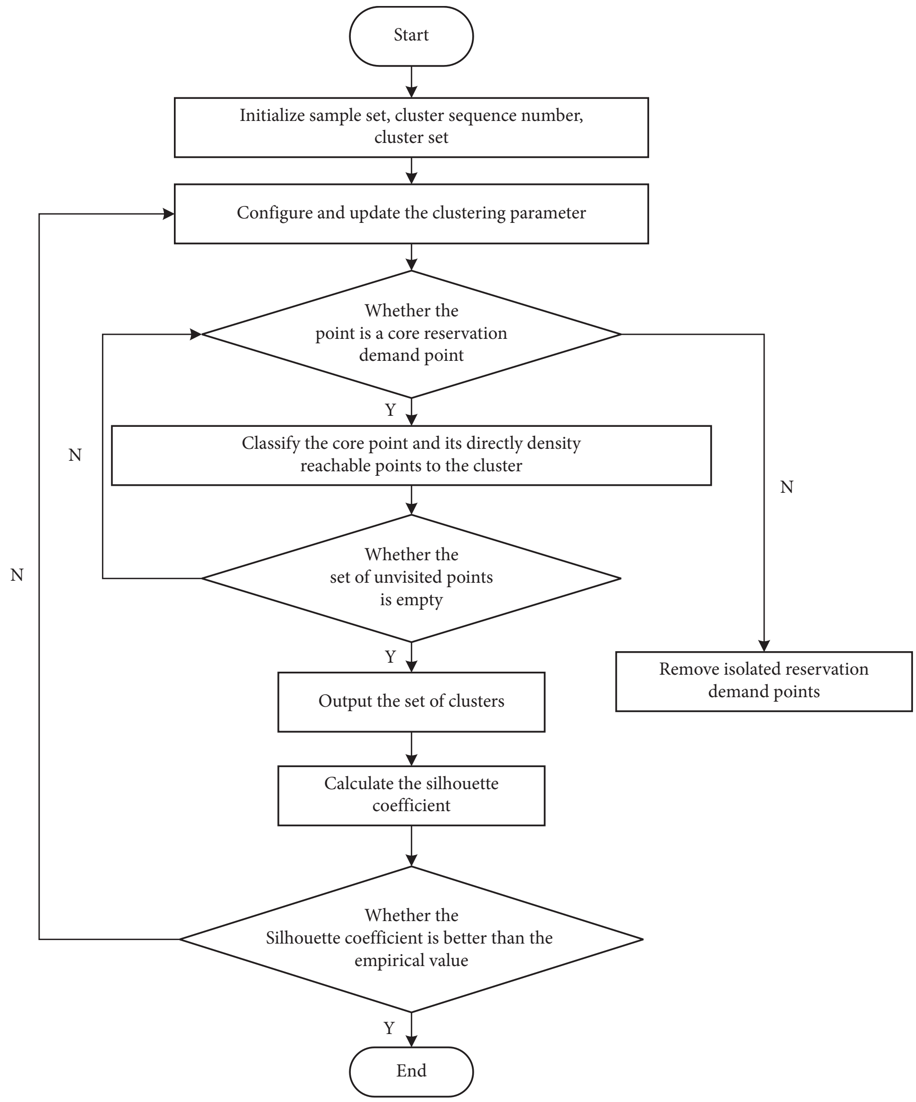

Figure 5: Workflow of the improved DBSCAN clustering algorithm.

Definition 2. Core reservation demand point. $|\varepsilon(p_i)|$ is the number of reservation points ε neighborhood of p_i, and $\min(\mathrm{Num})$ is the minimum number of passengers that are responded to. If $|\varepsilon(p_i)| \geq \min(\mathrm{Num})$, p_i is defined as the core reservation demand point.

Definition 3. Directly density reachability of the reservation demand point. If $p_i \in \varepsilon(p_j)$ and $|\varepsilon(p_j)| \geq \min(\mathrm{Num})$ hold between p_i and p_j, then p_i is considered directly density reachable from p_j.

The definitions of density reachability and density connection are the same as in the DBSCAN algorithm. Based on travel preference and the definitions, a DBSCAN clustering algorithm of reservation demand points with the silhouette coefficient as the evaluation indicator is constructed. Figure 5 shows the flow of the algorithm.

To sum up, the time preference sets M^a, M^b, and M^c are introduced into the algorithm to generate the departure location preference cluster sets P_m^a, P_m^b, and P_m^c as the alternative departure location preference clusters. P_m^a, P_m^b, and P_m^c are the sets of departure location clusters with a preference for fixed route transport, semifixed route transport, and flexible route transport, respectively. The meanings of the symbols within the algorithm and formula are detailed in the Table 2.

4.2. Arrival Location Preference DBSCAN Clustering. The arrival location preference is clustered, and the result is compared with the alternative sets. If there are intersections, the sample is classified into the set of dense points of spatiotemporal preference; if there are no intersections, it is classified into the set of discrete points of spatiotemporal preference for iteration and updating.

(1) According to descriptions in Section 4.1, M^a, M^b, and M^c are introduced to the algorithm to generate arrival location preference cluster sets $P_m^{a\prime}$, P_m^{b}, and $P_m^{c\prime}$, which are the arrival location cluster sets with preferences for fixed route transport, semifixed route transport, and flexible route transport, respectively;

Table 2: Definitions of variables.

Symbol	Meaning and format	Meaning of superscript/subscript and format	Location of appearance in the text
Q	Data of demand points		Table 1 in Section 3.1 of the text
P	Set of reservation demand points		
T	Set of departure time		
T'	Set of arrival time		
O	Set of departure location		
D	Set of arrival location		
Δ	Traveling preference priority		
p_i, p_j	Reservation demand point; italic and lower case	i and j are the serial number of the reservation demand points, italic and lower case	
t_i	Departure time of reservation demand point; italic and lowercase, unit: min	i is the serial number of the reservation demand point; italic and lowercase	
t_i'	Arrival time of reservation demand point; italic and lowercase, unit: min	i is the serial number of the reservation demand point; italic and lowercase	
(x_i, y_i)	Departure location of reservation demand point; italic and lowercase, unit: km	i is the serial number of the reservation demand point; italic and lowercase	
(x_i', y_i')	Arrival location of reservation demand point; italic and lowercase, unit: km	i is the serial number of the reservation demand point; italic and lowercase	
$\delta_i(a, b, c)$	Priority order of traveling preference of reservation demand point; italic and lowercase	i is the serial number of the reservation demand point; a, b, c represent the traveling preference of the fixed mode, the semifixed mode, and the flexible mode; italic and lowercase	
N^{ij}	Set of reservation point with the i-th traveling preference and j-th iteration of departure time; italic and uppercase	i is the serial number of traveling preference, j is the number of iterations, where $i \in (a, b, c)$ and $j \in (1, 2, 3, 4)$; italic and lowercase	Contents of Section 3.2 in the text
$S_{R_{ij}}$	Distance between clusters of reservation demand points calculated by the average linkage method; italic and uppercase, unit: min	i and j are the serial number of clusters of reservation demand points; italic, lowercase	Equation 1 in the text
R_i, R_j	Clusters of reservation demand points, and each cluster contains at least one reservation demand point; italic and uppercase	i and j are the serial number of reservation demand points; italic and lowercase	
n_{R_i}, n_{R_j}	The number of points in the reservation demand point cluster; italic and lower case	i and j are the serial number of reservation demand point clusters; italic and lowercase	
t_{R_i}, t_{R_j}	The departure time of a point in the reservation demand point cluster italic and lowercase, unit: min	i and j are the serial number of reservation demand point cluster; italic and lowercase	
τ	Time span; unit: min		Equation 2 in the text
M	The set of dense points with the same departure time preference; italic and uppercase		
G	The set of discrete points with the same departure time preference; italic and uppercase		
φ	Minimum number of passengers		Equation 3 in the text
z_i	The passenger capacity of the i -th means of transport; italic and lowercase	i is the serial number of traveling preference, where $i \in (a, b, c)$	
δ_i	The expected full load rate of the i -th means of transport; italic and lowercase	i is the serial number of traveling preference, where $i \in (a, b, c)$	
$N^{ij\prime}$	The set of reservation points with the i-th traveling preference and the j-th iteration of arrival time; italic and uppercase	i is the serial number of traveling preference, and j is the times of iterations, where $i \in (a, b, c)$, $j \in (1, 2, 3, 4)$; italic and lowercase	Contents of Section 3.3 in the text
G'	The set of discrete points with the same arrival time preference; italic and uppercase		
M'	The set of dense points with the same arrival time preference; italic and uppercase		Equation 4 in the text
S	The set of discrete points on the temporal dimension; italic and uppercase		
p_i^m	Reservation demand points in the dense point sets M and M'; italic and lowercase	i is the serial number of the reservation demand point; italic and lowercase	
p_i^g	Reservation demand points in the set of isolated points G and G'; italic and lowercase	i is the serial number of the reservation demand point; italic and lowercase	

Table 2: Continued.

Symbol	Meaning and format	Meaning of superscript/subscript and format	Location of appearance in the text
M^a	The set of dense points of the fixed transport mode in the time dimension italic and uppercase	a represents the traveling preference for the fixed mode of transport; italic and lowercase	Contents of Section 3.3 in the text
M^b	The set of dense points of the semifixed transport mode in the time dimension; italic and uppercase	b represents the traveling preference for the semifixed mode of transport; italic and lowercase	
M^c	The set of dense points of the flexible transport mode in the time dimension; italic and uppercase	c represents the traveling preference for the flexible mode of transport; italic and lowercase	
$\varepsilon(p_i)$	The set of all reservation demand points within a circle with p_i as the center and ε as the radius; italic and lowercase	i is the serial number of the reservation demand point; italic and lowercase	Contents of Section 4.1 and Equation 5 in the text
P	The set of reservation demand points within the sample; italic and uppercase		
$\text{dist}(p_i, p_j)$	The distance between two reservation demand points p_i and p_j; italic and lowercase, unit: km	i and j are the serial number of reservation demand points; italic and lowercase	
$\lvert\varepsilon(p_i)\rvert$	The number of reservation points within the ε neighborhood of p_i; italic and lowercase	i is the serial number of the reservation demand point; italic and lowercase	
$\min(\text{Num})$	The minimum number of passengers that are responded to		
P_m^a	The set of departure location clusters with a preference for the fixed transport mode; italic and uppercase	a represents the traveling preference for the fixed mode of transport; italic and lowercase	
P_m^b	The set of departure location clusters with a preference for the semifixed transport mode; italics and uppercase	b represents the traveling preference for the semifixed mode of transport; italic and lowercase	
P_m^c	The set of departure location clusters with a preference for the flexible transport mode; italics and uppercase	c represents the traveling preference for the flexible mode of transport; italic and lowercase	
$P_m^{a\prime}$	The set of arrival location clusters with a preference for the fixed transport mode; italics and uppercase	a represents the traveling preference for the fixed mode of transport; italics and lowercase	Contents of Section 4.2 and Equation 6 in the text
$P_m^{b\prime}$	The set of arrival location clusters with a preference for the semifixed transport mode; italics and uppercase	b represents the traveling preference for the semifixed mode of transport; italics and lowercase	
$P_m^{c\prime}$	The set of arrival location clusters with a preference for the flexible transport mode; italics and uppercase	c represents the traveling preference for the flexible mode of transport; italics and lowercase	
$M^{a\prime}$	The set of dense points of fixed transport mode in the spatiotemporal dimension; italics and uppercase	a represents the traveling preference for the fixed mode of transport; italics and lowercase	
$M^{b\prime}$	The set of dense points of semifixed mode in the spatiotemporal dimension; italics and uppercase	b represents the traveling preference for the semifixed mode of transport; italics and lowercase	
$M^{c\prime}$	The set of dense points of spatiotemporal preference for the flexible transport mode; italics and uppercase	c represents the traveling preference for the flexible mode of transport; italics and lowercase	
$M^{i\prime}$	The set of dense points of different spatiotemporal preferences; italics and uppercase	i is the serial number of traveling preference, and $i \in (a, b, c)$; italics and lowercase	
L	The set of discrete points of spatiotemporal preference italics and uppercase		

(2) $P_m^{a\prime}$, $P_m^{b\prime}$, and $P_m^{c\prime}$ are compared with the alternative sets P_m^a, P_m^b, and P_m^c. If there is an intersection, it is kept to the set of dense points, and if there is no intersection, it is divided into the set of discrete points, so as to obtain the result of time preference clustering The specific discriminant method was obtained with reference to the literature [16] and is as shown in the following expressions:

$$\begin{cases} p_j \in M^{i\prime} & P_m^i \cap P_m^{i\prime} \neq \varnothing,\ i = a, b, c, \\ p_j \in L & P_m^i \cap P_m^{i\prime} = \varnothing,\ i = a, b, c, \\ S \in L, \end{cases} \tag{6}$$

where p_j is the j-th reservation demand point; $M^{a\prime}$, $M^{b\prime}$, and $M^{c\prime}$ are the dense points sets with a spatiotemporal

Table 3: Simulation of reservation demand points.

P	T	T'	O	D	Δ
p_1	21.02	15.49	(0.2, 0.33)	(3.17, 3.49)	(b, a, c)
p_2	13.25	22.67	(1.47, 1.94)	(3.71, 3.33)	(c, b, a)
...	...	...	...	...	...
p_{60}	5.73	28.56	(1.07, 1.72)	(2.36, 2.71)	(c, b, a)

preference for fixed route transport, semifixed route transport, and flexible route transport, respectively; S is the set of time preference discrete points; and L is the set of spatiotemporal preference discrete points. In the MaaS system, the reservation points in L are assigned to flexible route transport, and $M^{i'}$ and L are updated through iteration. The meanings of the symbols within the algorithm and formula are detailed in the Table 2.

To conclude, spatial preference DBSCAN clustering is performed to obtain the spatiotemporal preference dense points set $M^{i'}$, and allocation of traffic resources according to different preferences can respond to the traffic needs of passengers.

4.3. Analysis of Spatiotemporal Preference Clustering Algorithm. Reservation demand points are affected by travel time and location, which makes their distribution uneven within space and time, and the effect of hierarchical clustering and the DBSCAN algorithm will be affected. The spatiotemporal preference class algorithm proposed in this study can improve the clustering effect and meet more travel demands by combining traveler preferences and transportation resource allocation methods on the basis of the MaaS system, which is analyzed as follows:

(1) Time preference hierarchical clustering: first, the uneven distribution of travel time has less impact on MaaS. MaaS can set different resource allocation schemes to meet different demands during peak and flat periods. Second, the time dimension hierarchical clustering proposed in this study determines the parameters and improves the clustering effect through various types of transportation characteristics within MaaS. Finally, those discrete points due to uneven distribution are assigned to reasonable transportation modes according to travel preferences to cluster again or meet their travel demands through online vehicles.

(2) Spatial preference DBSCAN clustering: first, the DBSCAN clustering parameters are limited by the service radius of traffic modes and the nuclear load and cannot change adaptively according to the distribution density of reservation demand points. Second, this algorithm uses the contour coefficient as an improvement index to enhance the clustering effect. Finally, the clustered discrete points with uneven spatial distribution are assigned reasonable transportation modes and clustered again according to the order of travel preference or their travel demand is satisfied by online appointment.

Table 4: Clustering results in different values of τ.

τ (min)	*Preference dense points*	
	Number of dense points	Percentage (%)
1	0	0
2	5	8.3
3	26	43.3
4	35	58.3
5	47	78.3
6	48	80
7	50	83.3
8	50	83.3
9	51	85
10	52	86.7
11	52	86.7
12	52	86.7
13	52	86.7
14	53	88.3
15	53	88.3
16	56	93.3

5. Example Analysis

5.1. Simulation Data. A simulation data set of reservation demand points is constructed: 60 reservation demand points are generated randomly; both the departure and arrival time is set within 30 min; the departure and arrival locations are within a 2 km $*$ 2 km rectangular area, respectively. Table 3 shows data of reservation demand points.

5.2. Example Clustering Analysis

(1) First of all, the dense points and discrete points of time preference are obtained through time preference hierarchical clustering. The minimum number of passengers φ based on the data for each type of vehicle in the MaaS model in Section 2.1 of this paper and equation (3) calculated according to different types of vehicles in the MaaS model is calculated as follows:

$$\varphi = \overline{\left\lceil \sum_i z_i \cdot \delta_i \right\rceil = \left\lceil \frac{3 \cdot 0.5 + 14 \cdot 0.5}{2} \right\rceil} = 5. \quad (7)$$

The clustering results at different values of time span τ is analyzed, as shown in Table 4.

As Table 4 shows, as τ increases, the number of dense points and its percentage among all points rise as well. There is a sharp increase in the number of dense points when $\tau = 3$ min and $\tau = 5$ min, and after τ reaches 10, the clustering result stabilizes. With both the passenger waiting time and the clustering result considered, we set $\varphi = 5$ persons and $\tau = 10$ min to obtain the clustering perception result, as shown in Table 5.

(2) Then, the silhouette coefficient is used to evaluate and analyze the parameters ε and min (Num) in the spatial preference DBSCAN clustering algorithm, as shown in Figure 6.

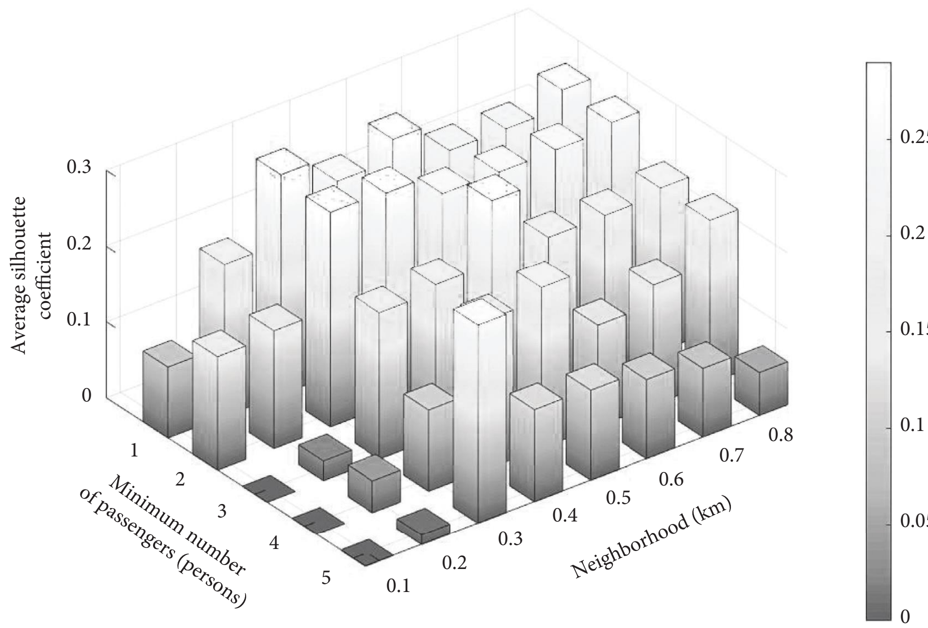

Figure 6: Spatial preference clustering parameters and silhouette coefficients.

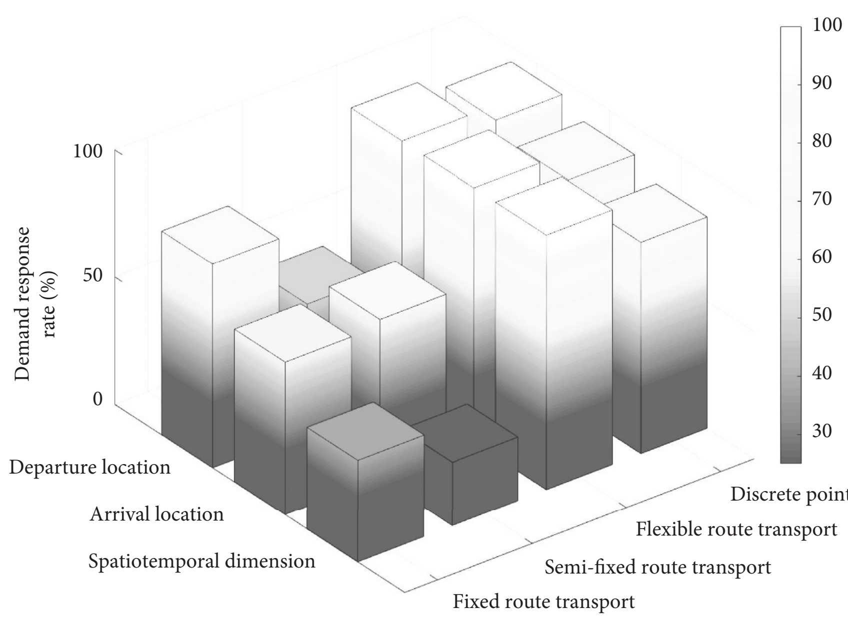

Figure 7: Spatiotemporal clustering results of different travel preferences.

Table 5: Time preference clustering result ($\varphi = 5$ and $\tau = 10\,\text{min}$).

Time preference sets	Reservation demand points included
M^a	$p_5, p_{36}, p_{39}, p_{47}, p_{53}$
M^b	$p_1, p_3, p_4, p_{12}, p_{32}, p_{37}, p_{40}, p_{41}$
M^c	$p_6, p_7, \ldots, p_{59}, p_{60}$
S	$p_2, p_{10}, p_{16}, p_{29}, p_{35}, p_{43}, p_{44}, p_{50}$

As Figure 6 shows, when $\min(\text{Num})$ remains constant, the silhouette coefficient first grows and then decreases as ε increases. When the value of ε is unchanged, the silhouette coefficient is negatively correlated to $\min(\text{Num})$. When $\varepsilon = 0.5km$ and $\min(\text{Num}) = 3$, the silhouette coefficient is 0.2836, which reaches the best clustering effect.

When $\varepsilon = 0.5km$ and $\min(\text{Num}) = 3$, we perform spatial preference DBSCAN clustering of M^a, M^b, and M^c, as well as all reservation demand points in S, as shown in Figure 7.

As Figure 7 shows, temporal dense points of different travel preferences are clustered and responded on the departure and arrival points to obtain $M^{i\prime}$ and L. According to the features of MaaS, the reservation points within S and L are assigned to flexible route transport for re-clustering to obtain the spatiotemporal clustering response result. The

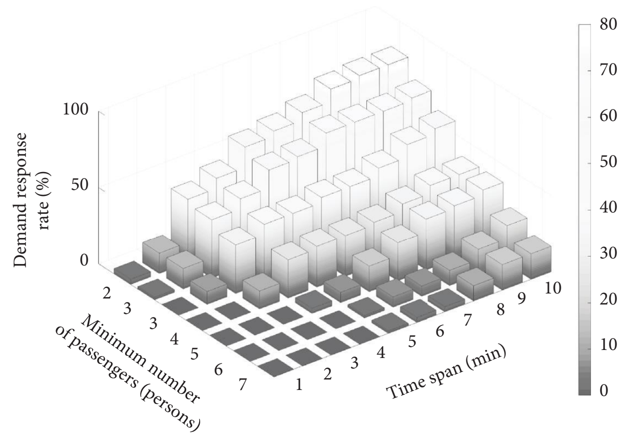

Figure 8: The demand response rate of hierarchical clustering.

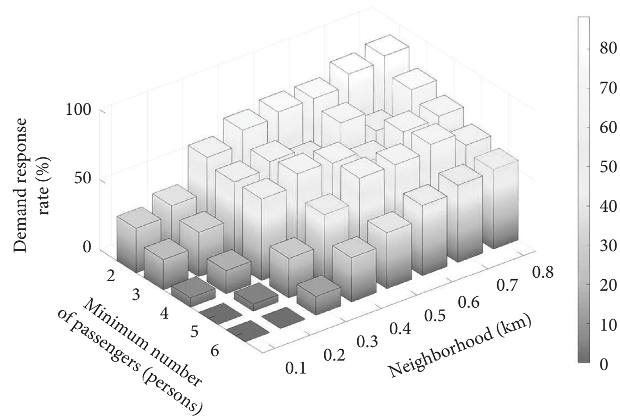

Figure 9: emand response rate of DBSCAN clustering.

Table 6: Spatiotemporal preference clustering result in the MaaS system.

Spatiotemporal preference sets	Reservation demand points included
$M^{a'}$	p_5, p_{39}
$M^{b'}$	p_4, p_{40}
$M^{c'}$	p_1, $p_2 \cdots\cdots$ p_{59}, p_{60}
L	p_{37}, p_{47}, p_{50}

ratio of dense reservation points to all reservation points is defined as the demand response rate for evaluation. The spatiotemporal demand response rate of fixed route transport, semifixed route transport, and flexible route transport is 40%, 25%, and 100%, respectively. Coordination by the MaaS system can respond to 83% of all discrete points, which considerably improves the overall response rate of the model. Table 6 shows the spatiotemporal preference clustering result in the MaaS system.

As Table 6 shows, there are 57 reservation demand points in the MaaS TDR model based on spatiotemporal preference clustering, and different means of transport are allocated as per the preferences and the response rate is 95%. Meanwhile, flexible route transport is allocated to meet the travel demand of three spatiotemporal discrete points based on the the MaaS system features, thereby achieving full demand coverage.

5.3. Model Evaluation

(1) Based on the example data, hierarchical clustering and DBSCAN clustering are performed to respond to travel demand, and the clustering effect is compared with our model, as shown in Figure 8 and Figure 9.

As Figures 8 and 9 show, hierarchical clustering and DBSCAN clustering achieve a maximum response rate of 80% and 88.3%, respectively. Our model, however, achieves a response rate of 95%, which is 15% and 6.7% higher than the other two.

Table 7: Results of spatiotemporal preference clustering for 10 groups of data.

Data serial number	Demand response rate (%)
Data 1	90
Data 2	90
Data 3	88.3
Data 4	93.3
Data 5	91.7
Data 6	95
Data 7	93.3
Data 8	86.7
Data 9	96.7
Data 10	88.3

Table 8: Results of spatiotemporal preference clustering for different numbers of reservation demand points.

Number of points	ε (km)	min (Num) /person	Demand response rate (%)
30	0.8	2	66.6
40	0.6	2	72.5
50	0.6	3	80
60	0.5	3	93.3
70	0.5	3	94.3
80	0.5	4	95
90	0.4	4	95.5
100	0.4	5	96

Table 9: Comparison of demand response rates of customized bus model.

Parameter		Indicator	Optimization by our model (%)
ε (km)	min (Num)/person	The demand response rate of the customized bus model (%)	
0.4	4	75	20
0.4	3	78.3	16.7
0.5	4	80	15
0.5	3	83.3	11.7
0.5	2	86.7	8.3

(2) A new appointment demand point simulation database is constructed, and 10 sets of data are randomly generated, each containing 60 reservation demand points. The results of spatiotemporal preference clustering for the 10 data sets are shown in Table 7.

As shown in Table 7, the spatiotemporal preference clustering algorithm proposed in this study can respond to most of the travel demands. The mean value of the simulation results for the 10 sets of data was obtained and the mean value of the response rate was 91.3%. Combining the MaaS to assign discrete points to flexible route transport can achieve full coverage of travel demand.

A database containing 100 reservation demand points is constructed, and each of the 30 to 100 demand points is selected to form 8 sets of data. The results of spatiotemporal preference clustering for different numbers of appointment demand points are shown in Table 8.

As shown in Table 8, the clustering parameters ε are negatively correlated with the number of reservation demand points. Moreover, the min (Num) show a positive correlation with the reservation demand point. The response rate of travel demand grows with the density of reservation demand points, which means that the more users of MaaS, the more its clustering response effect and transportation service are improved.

(3) Based on the example data, the spatiotemporal clustering model under the customized bus mode [16] is used to respond to travel demand, and the result is compared with our model, as shown in Table 9.

Calculation shows that the spatiotemporal clustering model under the customized bus mode achieves the optimal response rate at 86.7%. The demand response rate of this model is improved by 8.3% compared to that for the same data. Compared with customized buses, the MaaS system attends to travel preferences and coordinates different means of transport, which better meets the travel demand of reservation demand points and improves the response rate and comfortability.

5.4. Model Applicability Analysis. MaaS is a system for coordinating multiple modes of transportation to address the travel needs of travelers and the imbalance between the supply and demand of transportation resources. Due to the inconsistent level of economic development in each country and region, factors such as the proportion of various types of transportation, road conditions, and the level of public transportation services vary. Developed countries or economically developed regions have better road conditions, better public transportation, and higher per capita motor vehicle ownership. The MaaS model proposed in this study includes public transportation, customized public transportation, and online transportation, which correspond to fixed, semifixed, and flexible route transport modes, respectively. The proposed spatiotemporal preference clustering algorithm also relies on the flexible transportation mode to solve the discrete state reservation demand points. Therefore, the MaaS model and clustering algorithm proposed in this study are suitable for areas where the above three types of transportation modes exist and the companies providing transportation services can integrate and coordinate.

As the example shown in Section 5 of this paper, its simulation data are only related to spatiotemporal information and travel preference priorities, and there is no influence of external factors (road network conditions and environment.). The application of the spatiotemporal preference clustering algorithm proposed in this study in the algorithm case can satisfy the travel demand of travelers. Therefore, this algorithm has some applicability in regions or countries that have the ability to build the above MaaS model.

6. Conclusions

MaaS is an emerging transportation system that coordinates various transportation modes and provides high-quality transportation services. Quantitative analysis of MaaS has become one of the current research hotspots. To solve the problem of traffic demand response under MaaS mode, this paper designs a spatiotemporal preference clustering algorithm and constructs a traffic demand response model under the MaaS model based on the spatiotemporal distribution of traffic demand and travel preference.

This study constructs a MaaS model based on fixed, semifixed, and flexible route transport. It collects travel demand data through a web platform and coordinates the allocation of transportation resources with reference to the spatial and temporal distribution of data points and travel preferences of travelers. It can improve the utilization of transportation resources and alleviate the imbalance between the supply and demand of urban transportation resources. Based on the discussion of the simulation example, it is clear that the MaaS model constructed in this study has a high demand response rate and applies to many areas with the above three transportation modes.

The spatiotemporal preference clustering algorithm designed in this study combines the travel preferences of travelers to cluster the demand point response for reservations in both temporal and spatial dimensions. The algorithm has a large improvement in the clustering response of demand points compared with hierarchical clustering and DBSCAN clustering algorithms. The introduction of travel preference factors not only improves the clustering response but also improves the service quality. According to the discussion of the simulation example, the MaaS model using a spatiotemporal preference clustering algorithm can effectively cluster and reasonably allocate transportation resources compared with customized public transportation. In summary, this study provides the corresponding support and theoretical research basis for the construction and application of the MaaS model.

Current models and algorithms still have shortcomings; the spatiotemporal dynamic distribution of demand points can be considered to improve the algorithm, and the generic cost function is employed to optimize such parameters as travel preference and walking distance to obtain a travel demand model of higher efficiency and comfortability under the MaaS system.

Data Availability

All data, models, and code generated or used during the study appear in the submitted article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] S. Hietanen, "Mobility as a service," *The New Transport Model*, vol. 12, no. 2, pp. 2–4, 2014.

[2] MaaS Alliance, *Guidelines & Recommendations to Create the Foundations for a Thriving MaaS Ecosystem*, MaaS Alliance, Brussels, Belgium, 2017.

[3] M. Kamargianni, W. Li, M. Matyas, and A Schafer, "A critical review of new mobility services for urban transport," *Transportation Research Procedia*, vol. 14, pp. 3294–3303, 2016.

[4] S. A. Shaheen and A. P. Cohen, "Carsharing and personal vehicle services: worldwide market developments and emerging trends," *International Journal of Sustainable Transportation*, vol. 7, no. 1, pp. 5–34, 2013.

[5] X. L. Liu, H. D. Liu, and X. J. Li, "Framework and developing roadmap of MaaS (mobility as a service) in China," *Transportation Research*, vol. 5, no. 3, pp. 1–9, 2019.

[6] ATKINS, *Journeys Of the Future-Introducing Mobility as a Service*, ATKINS, London, UK, 2015.

[7] P. Jittrapirom, V. Caiati, A. M. Feneri, S. Ebrahimigharehbaghi, M. J. A. Gonzalez, and J Narayan, "Mobility as a service: a critical review of definitions, assessments of schemes, and key challenges," *Urban Planning*, vol. 2, no. 2, pp. 13–25, 2017.

[8] LEK Consulting, *Mobility as a Service: The Next Transport Disruption*, LEK Consulting, Boston, MA, USA, 2017.

[9] S. Djavadian and J. Y. J. Chow, "An agent-based day-to-day adjustment process for modeling 'Mobility as a Service' with a two-sided flexible transport market," *Transportation Research Part B: Methodological*, vol. 104, pp. 36–57, 2017.

[10] M. Kamargianni and M. Matyas, "The business ecosystem of mobility-as-a-service," in *Proceedings of the 96th Annual Meeting of the Transportation Research Board*, Transportation Research Board, Washington, DC, USA, January 2017.

[11] CEDR, *Deliverable 3: Business and Operator Models for MaaS. MAASiFiE Project Funded by CEDR*, VTT Technical Research Centre of Finland Ltd, Helsinki, Finland, 2016.

[12] M. Audouin and M. Finger, "The development of Mobility-as-a-Service in the Helsinki metropolitan area: a multi-level governance analysis," *Research in Transportation Business & Management*, vol. 27, pp. 24–35, 2018.

[13] J. Brake, J. D. Nelson, and S. Wright, "Demand responsive transport: towards the emergence of a new market segment," *Journal of Transport Geography*, vol. 12, no. 4, pp. 323–337, 2004.

[14] F. Errico, T. G. Crainic, F. Malucelli, and M. Nonato, "A survey on planning semi-flexible transit systems: m," *Transportation Research Part C: Emerging Technologies*, vol. 36, pp. 324–338, 2013.

[15] F. Qiu, W. Li, and J. Zhang, "A dynamic station strategy to improve the performance of flex-route transit services," *Transportation Research Part C: Emerging Technologies*, vol. 48, pp. 229–240, 2014.

[16] H. N. Xue and J. Wang, "Demand response mechanism of customized bus based on space-time clustering," *Journal of Highway and Transportation Research and Development*, vol. 38, no. 3, pp. 113–121, 2021.

[17] J. Sochor, H. Strömberg, and I. C. M. Karlsson, "Implementing mobility as a service: challenges in integrating user, commercial, and societal perspectives," *Transportation Research Record Journal of the Transportation Research Board*, vol. 2536, no. 1, pp. 1–9, 2015.

[18] M. Matyas and M. Kamargianni, "A stated preference experiments for mobility-as-a-service plans," in *Proceedings of the IEEE International Conference on Models & Technologies for Intelligent Transportation Systems*, pp. 738–743, IEEE, Naples, Italy, June 2017.

[19] C. Q. Ho, D. A. Hensher, M. Corinne, and Z. W. Yale, "Potential uptake and willingness-to-pay for Mobility as a Service (MaaS): a stated choice study," *Transportation Research Part A Policy & Practice*, vol. 117, pp. 302–318, 2018.

[20] X. L. Lu, X. Zhang, and J. Yu, "Research of a comprehensive evaluation method for customized flexible transit system," *Journal of Highway and Transportation Research and Development*, vol. 32, no. 5, pp. 135–140, 2015.

[21] Q. Fan, W. Wang, X. D. Hua, and X. Y. Wei, "Dominant transportation distance for multi transportation modes in urban integrated transportation network based on general travel costs," *Journal of Transportation Systems Engineering and Information Technology*, vol. 18, no. 4, p. 7, 2018.

[22] F. Murtagh and P. Contreras, "Algorithms for hierarchical clustering: an overview," *Wiley Interdisciplinary Review: Data Mining and Knowledge Discovery*, vol. 2, no. 1, pp. 86–97, 2012.

[23] G. Wang and G. Y. Lin, "Improved adaptive parameter DBSCAN clustering algorithm," *Computer Engineering and Applications*, vol. 56, no. 14, pp. 45–51, 2020.