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Online shop location optimization using a fuzzy multi-criteria decision model—Case study on Taobao.com

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ABSTRACT

The solution to location optimization for an E-service network is a difficult, complex, tedious, and protracted process which requires evaluation to be made on a number of aspects according to certain criteria. This paper proposes an online shop location optimization method which combines a fuzzy location choice method based on neighborhood infrastructure with a fuzzy multi-criteria decision-making (FMCDM) method. The study process includes two stages. The first stage identifies the location choice characteristics for online shops selling digital products, and provides candidate sites for further location optimization consideration. The second stage incorporates the information provided by two experts leading to fulfillment of the selection of optimum locations. The research findings are as follows: (1) The location choices of online shops which sell valuable goods, such as digital products, are mainly aggregated and still rely on traditional neighborhood infrastructure. The selection of an optimum location is a process of transference from overlap locations to complete locations. (2) Online shop location optimization can be modeled and calculated by fuzzy numbers to handle uncertain data. The research findings have shown that the proposed fuzzy location choice method and the FMCDM method have a well-structured architecture and a great computational power. It helps to promote decision-making quality in decision-making processes under uncertainty.

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1. Introduction

The study of the location optimization of an E-service network in an urban area is a common topic in deciding whether a geographical location exists or not, and the location's manifestation in half virtual, half real period [3]. It plays a significant role in regional economic development and the improvement of people's living standards, but the current state and impact factors of location optimization have not been clear until now. During its early development, online shopping was regarded as a technology that would eliminate location by changing shopping practices and the sites of traditional shops [5,27]. Hashimoto [9], Wilson [26] and Lu and Lu [16] offer different perspectives in their case studies of information networks in virtual space and their corresponding geographical location. Subsequent studies have indirectly discussed the new characteristics of location optimization from different perspectives; for example, location restriction and the spatial competition of E-service networks, and location selection that is influenced by information technology under information industry agglomeration. In further studies, Lu and Fan [18] and Han and Lu [7] directly explored the location changes and relations between new commercial modes and geographical locations in the information age by studying outdoors and traveling websites. Overall, as all services, transactions, payments and many other activities can be carried on in virtual space [1], E-service network location optimization is becoming more complex whether the impacts of online shopping are magnified or not. The relevant empirical studies provide general conclusions, but they lack regular understanding and explicit analysis of the characteristics of E-service network location choice and location optimization.

Creating new approaches to manage regions is driven by changing requirements, so location choice research methods are being developed fast. Jiven and Larkham [13] and Billig [4] have suggested developing more location choice concepts, which could build a theoretical basis for the innovative study of E-service network location. If the issue is narrowed to a study of the location choice of an online shop within a city, many approaches would be helpful; for example, the approach of the expanding network positioning service proposed by Arai and Sugizaki [2], the approach of building positioning system in small regions by Sten [24], and the holographic regional structuring approach of the distribution

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pattern of the service industry and service activity location by Wang and Li [25]. According to ideas on absorbing local atmosphere to form location choice, it is possible to formulate an approach based on the fuzzy location choice approach of neighborhood infrastructure to evaluate the location choice of an E-service network.

The research method of location optimization has also undergone development. The primary approach conducts suitability and statistical analyses by using thematic map overlays [20] to screen candidate sites and study geographical impacts. With the advance of geographical information systems (GIS) technology, the site selection process increasingly relies on more sophisticated spatial mapping analysis. Jensen and Christensen [12] demonstrated the use of a raster-based GIS with its associated Boolean logic map algebra to identify the impact of the geographical factor on potential sites, while Keir et al. [14] put forward a full-scale site selection process of raster-based and vector-based GIS. In an empirical study, Sener et al. [23] solved the site selection problem by ranking the potential areas based on a number of spatial information criteria. In summary, the method of processing spatial information by using GIS, overlaying the maps, composing a region system with two distinct types of regions which contain the area outside and inside the intersected boundaries respectively, and then screening the candidate sites based on ranking selection criteria, is effective.

Multi-criteria decision-making (MCDM) methods can assist in identifying the optimal location of candidate sites; for example, the analytic hierarchy process (AHP) [11,21] is a useful analytical tool for optimization, which can explicitly rank tangible and intangible criteria for the purpose of selecting priorities, and is widely utilized to solve the optimization problems of candidate sites. The major difficulty the basic MCDM faces is in estimating the required input data, because it does not take into account the uncertainty of a person's judgment. To overcome the shortcomings, fuzzy set principle is introduced to integrate MCDM for the selection of the best alternative [28]. The fuzzy membership function of fuzzy set theory has properly described the uncertainties in a complex decision-making process. The practical applications of FMCDM have shown advantages in handling unquantifiable problems [6,29,10]. FMCDM utilizes fuzzy numbers to aggregate the decision makers' subjective assessment on criteria weightings and the appropriateness of alternative candidate sites versus the selection criteria to obtain the final scores-fuzzy appropriateness indices.

This paper presents a two-stage synergic analysis approach for the location optimization of candidate sites. In the first stage, potential candidate sites are found via initial screening, and the location choice characteristics are evaluated by analyzing locating factors and criteria. In this stage, the analysis can be carried out by using the geographical data of a GIS thematic map. In the second stage, FMCDM is used as a tool for identifying location optimization and eventually generating a ranking of all candidate sites in preference order.

The cases selected in this paper are Shanghai, Shenzhen, Tianjin, and Beijing, which constitute the major industrial bases, financial centers, information centers, business centers, transit centers, and tourist attractions of China. Online shops were set up at a relatively early stage in these cities, and are now quite widespread; also, online shops in these cities are highly developed and have the biggest numbers in the country. The online shops in these cities present special distribution characteristics. This paper tries to reveal E-service network location choice characteristics and to explore location optimization and potential impact factors based on the spatial agglomeration of online shops on Taobao.com in four main cities in China.

The rest of this paper is organized as follows: Section 2 presents the preliminary on the FMCDM. Section 3 describes the proposed online shop location optimization method. It first selects and identifies the candidate sites, then uses FMCDM to calculate location optimization. Section 4 presents a case study on Taobao.com. Section 5 concludes this paper and outlines the significance of this study.

2. Preliminary

In this section, the fuzzy multi-criteria group decision-making method [17] is described. This method is composed of 10 steps on three levels.

Level one: Determine the expression and weights of evaluation aspects and evaluators (Steps 1–3).

Step 1: Determine the expression of evaluators and evaluation aspects.
Suppose an evaluation group with n evaluators $E = \{E_1, E_2, \ldots, E_n\}$, an alternative set with m alternatives $L = \{L_1, L_2, \ldots, L_m\}$ $(m \geqslant 2)$, and a criteria set with k evaluation aspects $C = \{C_1, C_2, \ldots, C_k\}$.

Step 2: Determine weights of evaluation aspects/criteria.
Let $W = \{W_1, W_2, \ldots, W_k\}$ be the weights of aspects in the model, where $W_i \in \{Absolutely\ unimportant, Unimportant, Less\ important, Important, More\ important, Strongly\ important, Absolutely\ important\}$. These weights are described by fuzzy numbers $\tilde{a}_1, \tilde{a}_2, \ldots, \tilde{a}_7$, respectively, where $\tilde{a}_1 < \tilde{a}_2 < \cdots < \tilde{a}_7$.

Step 3: Determine weights (importance degrees) of evaluators.
Let $V = \{v_1, v_2, \ldots, v_n\}$ be the weights of evaluators in the model, where $v_i \in \{Normal, Important, More\ important, and\ Most\ important\}$. These weights are described by fuzzy numbers $\tilde{b}_1, \tilde{b}_2, \tilde{b}_3, \tilde{b}_4$ respectively, where $\tilde{b}_1 < \tilde{b}_2 < \tilde{b}_3 < \tilde{b}_4$.

Level two: Individual preference generation (Steps 4–6).

Step 4: Set up the relevance degree (scores) of each alternative on each criterion.
The relevance degree of aspect C_i on alternative L_x set up by evaluator E_y is S_{xiy}, where $S_{xiy} \in \{Absolutely\ poor, Very\ poor, Poor, Fair, Good, Very\ good, Absolutely\ good\}$. These linguistic terms are described by fuzzy numbers $\tilde{c}_1, \tilde{c}_2, \ldots, \tilde{c}_7$, respectively, where $\tilde{c}_1 < \tilde{c}_2 < \cdots < \tilde{c}_7$.

Step 5: Calculate the relevance degrees of all the alternatives.
The relevance degree F_{xy} on the alternative L_x according to evaluator E_y is calculated by using

$$F_{xy} = \sum_{i=1}^{k} W_i \times S_{xiy}, \quad x = 1, \ldots, m;\ y = 1, \ldots, n.$$

Step 6: Normalize the relevance degrees.
The relevance degrees F_{xy}, $x = 1, \ldots, m$; $y = 1, \ldots, n$, are normalized by

$$\overline{F}_{xy} = \frac{F_{xy}}{\sum_{s=1}^{m} F_{sy_0}^{R}}, \quad x = 1, \ldots, m;\ y = 1, \ldots, n.$$

Level three: Group aggregation for final ranking (Steps 7–10).

Step 7: Normalize the weights of evaluators.
The normalized weight of E_y $(y = 1, 2, \ldots, n)$ is denoted as

$$\bar{v}_y = \frac{v_y}{\sum_{s=1}^{n} v_{s_0}^{R}}, \quad y = 1, \ldots, n.$$

Step 8: Calculate normalized weighted fuzzy decision vector.
Considering the normalized weights of all evaluators, we can construct a normalized weighted fuzzy decision vector

$$(F_1, F_2, \ldots, F_m) = (\bar{v}_1, \bar{v}_2, \ldots, \bar{v}_n) \begin{pmatrix} \overline{F}_{11}, \overline{F}_{21}, \ldots, \overline{F}_{m1} \\ \overline{F}_{12}, \overline{F}_{22}, \ldots, \overline{F}_{m2} \\ \cdots \\ \overline{F}_{1n}, \overline{F}_{2n}, \ldots, \overline{F}_{mn} \end{pmatrix}$$

where $F_i = \sum_{j=1}^{n} \overline{v}_j \times \overline{F}_{ij}$.

Step 9: Calculate distances between normalized weighted fuzzy decision vector and the positive-ideal and the negative-ideal values, respectively.

Fi is normalized and its range belongs to the closed interval [0,1]. We can then define a fuzzy positive-ideal solution (FPIS,F^*) and a fuzzy negative-ideal solution (FNIS,F^-) as:

$$F^* = 1 \quad \text{and} \quad F^- = 0.$$

The distance between each F_i and F^*, F_i and F^- can be calculated as:

$$d_i^* = d(F_i, F^*) \quad \text{and} \quad d_i^- = d(F_i, F^-), \quad i = 1, 2, \ldots, m.$$

where $d(\cdot)$ is the distance between two fuzzy numbers.

Step 10: Select the best alternative.

To determine the ranking order of all candidate sites, a closeness coefficient is defined as:

$$CC_i = \frac{1}{2}(d_i^- + (1 - d_i^*)), \quad i = 1, \ldots, m$$

The alternative that corresponds to Max(CC_i, $i = 1, \ldots, m$) is the most suitable one.

3. Online shop location optimization method

3.1. Identification of candidate sites

Candidate sites can be identified by fuzzy location choice method in this section, and candidate sites can be taken as the basis of location optimization research. The process of identification of candidate sites is composed of five steps on three levels.

Level one: Object selection (Step1).

Step 1: Obtaining online shop samples and their locations.

The appearance of E-commerce network brought online shops to the real world, i.e. products are sold in real entity shops, and information is released and transacted in virtual online shops. Both of the real entity shops and virtual online shops popularize each other and market products by customers' trust. In consequence, a totally new commerce has been formed. The online shops of E-commerce network can be divided into star level, diamond level, crown level, and gold crown level according to their accumulated points. They also can be divided into "has entity shop" and "no entity shop". The information of various shops can be got according to their goods categories by using the advanced search function of the E-commerce network, and the location data can be obtained by seeking entity shop location in "my shop", "shop announcement", "shop message", and "product introduction" after entering the home page of the online shops.

Level two: Condition definition (Steps 2–4).

Step 2: Defining the goods categories.

There are various goods categories of online shops in E-commerce network, generally including virtual, digital products, home, collection, clothing, skincare, food, service, recreation and sports, auction and others. The goods categories can be selected to study according to actual needs. Considering that virtual goods do not need the support of entity shops, and auction and others cover too broad, they are not taken as study objects of goods categories of online shops.

Step 3: Defining neighborhood infrastructure.

Neighborhood infrastructure gives aid to the study of location choice and location optimization of online shops. Schriner [22] and Lu et al. [15] have studied the impact of E-commerce development on selecting entity shop locations for companies in microcosmic perspective, and suggested that E-commerce companies consider not only traditional factors, but also new ones, such as easy attracting "taste group" and accessing to professional services, on location choice problem. Based on the former study [8], influence factors of online shop location choice can be roughly divided into commercial downtown area, near stadiums, transportation center, large living community, and near education base. These five aspects can be taken as the neighborhood infrastructures for online shop location choice.

Step 4: Classification of location types.

The former study [8] has proved that "region segmentation" analysis is an effective method for location choice formalization and location optimization. Three main aspects of expressing fuzzy location by region segmentation are spatial object, proximity of this spatial object in a segmental region, and quantizing the object. Fuzzy location can be described as a relation form of section region, i.e. one spatial object of one region segmentation exists in this region segmentation. According to the purpose of study, fuzzy location expression can be explicated. First, define an influence factor as center to create coordinate; and then distinguish the segmental regions to form "region segmentation"; finally, estimate whether the region belong to the influence range or not.

According to the golden law of commercial real estate trade zone, there are several layers in trade zone, in which primary trade zone is the central area of commercial consumption. Its radiation radius is about 1–2 km [30]. On the basis of this law, radiation radius of the primary trade zone can be set as 1 km and 2 km, which can be respectively considered as the radius of inner circle and outer circle of neighborhood infrastructure. Thus, two circles are formed with neighborhood infrastructure as center, i.e. inner layer and outer layer. Then according to the maps of four sample cities which are published by China Map Publishing House, radiation region of two layers of neighborhood infrastructure in city map can be got by scale conversion.

The online shops in radiation region of one layer of neighborhood infrastructure can be considered as being influenced by this layer. In order to define a fuzzy location of spatial object in a segmental region, four representations of complete location, overlap location, transitional location, and incomplete location are made. Complete location is where marker of online shops influenced by one neighborhood infrastructure in its inner layer. Overlay location is the marker influenced by two or more neighborhood infrastructures in their inner layer. Transitional location is the marker influenced by one neighborhood infrastructure in its outer layer. Incomplete location is where out of the influence of neighborhood infrastructure in its two layers.

Level three: Provide candidate sites (Step 5).

Step 5: Identification of candidate sites.

According to the influences of five neighborhood infrastructures mentioned above, the numbers of online shops under the selected category falling into different location types can be got. The ratios of the online shops under this category of different location types to the total online shops under all categories can be calculated. By marking the online shops' positions on the city maps of different neighborhood infrastructures under the condition of neighborhood infrastructure coordinate point and segmental region, the distribution map of online shops under this category can be obtained, and then the distribution map of candidate sites for the location optimization can be generated by integrating different layers.

3.2. Calculation of location optimization

Due to the difficulties of quantifying the impacts of neighborhood infrastructure on the location optimization of online shops, the FMCDM method [17] is chosen. This method applies fuzzy-sets techniques to deal with linguistic terms used in the weights of criteria, the weights of decision-making experts, and the evaluation scores given by experts. The general model of FMCDM has been widely used in the decision-making process. Based on previous experience, triangular fuzzy numbers can express the impact weight of online shops location optimization via neighborhood infrastructure. An MCDM-based group aggregation technique is applied to finally rank all candidate sites, and the optimum location is selected by the ranking.

The method is composed of 10 steps on three levels.

Level one: Determine the expression and weights of evaluation aspects and experts (Steps 1–3).

Step 1: Determine the expression of experts and evaluation aspects.

Let E be the set of n decision-making experts, L be the set of m candidate sites, C be the set of k impact factors of neighborhood infrastructure.

Step 2: Determine weights of evaluation aspects/criteria.

The experts make impact weights W_{tj} ($t = 1,2,\ldots,k$; $j = 1,2,\ldots,n$) of k neighborhood infrastructures on m candidate sites, i.e. let W_{tj} be the weight given to C_t (the tth criteria) by expert E_j, where $W_{tj} \in \{$*Absolutely unimportant, Unimportant, Less important, Important, More important, Strongly important, Absolutely important*$\}$. These weights are described by triangular fuzzy numbers as shown in Table 1.

Step 3: Determine weights (importance degrees) of experts.

Experts play different roles and have different degrees of influence on the ranking of the candidate sites. Some members' preferences and opinions are more important than others for a specific evaluation. Therefore, in the method, each evaluator is assigned a weight based on their importance in ranking the set of candidate sites. Let $V = \{v_1, v_2, \ldots, v_n\}$ be the weights of experts in the model, where $v_i \in \{$*Normal, Important, More important,* and *Most important*$\}$. The weights of experts are determined through discussions in the group or assigned by a higher management level before the evaluation process takes place. The weight terms are described by triangular fuzzy numbers as shown in Table 2.

Level two: Individual preference generation (Steps 4–6).

Step 4: Set up the relevance degree (rating scores) of each candidate site on each criterion.

The importance of the neighborhood infrastructures towards the candidate sites are ranked by experts with linguistic terms.

Table 1
Linguistic variables for describing the weights of each neighborhood infrastructure.

Linguistic variables	Fuzzy numbers
Absolutely unimportant	(0,0,0.1)
Unimportant	(0,0.1,0.3)
Less important	(0.1,0.3,0.5)
Important	(0.3,0.5,0.7)
More important	(0.5,0.7,0.9)
Strongly important	(0.7,0.9,1)
Absolutely important	(0.9,1,1)

Table 2
Linguistic variables for describing the weights of evaluators.

Linguistic variables	Fuzzy numbers
Normal	(0,0.25,0.5)
Important	(0.25,0.5,0.75)
More important	(0.5,0.75,1)
Most important	(0.75,1,1)

Table 3
Linguistic variables for describing the evaluators' ratings.

Linguistic variables	Fuzzy numbers
Absolutely poor	(0,0,0.1)
Very poor	(0,0.1,0.3)
Poor	(0.1,0.3,0.5)
Fair	(0.3,0.5,0.7)
Good	(0.5,0.7,0.9)
Very good	(0.7,0.9,1)
Absolutely good	(0.9,1,1)

Let S_{itj} be the rating score assigned to candidate sites A_i by expert E_j under criterion C_t, where $S_{itj} \in \{$*Absolutely poor, Very poor, Poor, Fair, Good, Very good, Absolutely good*$\}$. These ratings are described by triangular fuzzy numbers as shown in Table 3.

Step 5: Calculate the fuzzy appropriateness indices of all the candidate sites.

The fuzzy appropriateness index of candidate site A_i according to expert E_j, F_{ij} is calculated by using

$$F_{ij} = \sum_{t=1}^{k} W_{tj} \times S_{itj}, \quad i = 1,\ldots,m;\ j = 1,\ldots,n, \tag{1}$$

Step 6: Normalize the fuzzy appropriateness indices.

F_{ij}, $i = 1,\ldots,m$; $j = 1,\ldots,n$, are normalized by

$$\overline{F}_{ij} = \frac{F_{ij}}{\sum_{s=1}^{m} F^R_{sj_0}}, \quad i = 1,\ldots,m;\ j = 1,\ldots,n, \tag{2}$$

Level three: Group aggregation for final ranking (Steps 7–10).

Step 7: Normalize the weights of experts.

Each expert E_j has been assigned a weight v_j, $j = 1,\ldots,n$. The normalized weight of E_j is denoted as

$$\bar{v}_j = \frac{v_j}{\sum_{s=1}^{n} v^R_{s_0}}, \quad j = 1,\ldots,n, \tag{3}$$

Step 8: Calculate normalized weighted fuzzy appropriateness indices of candidate sites.

The final fuzzy appropriateness index of candidate site A_i aggregating all experts' opinions, F_i is computed by

$$F_i = \sum_{j=1}^{n} \bar{v}_j \times \overline{F}_{ij}, \quad i = 1,\ldots,m, \tag{4}$$

Step 9: Calculate distances between normalized weighted fuzzy appropriateness indices and the positive-ideal and the negative-ideal values, respectively.

F_i is normalized and its range belongs to the closed interval [0,1]. We can then define a fuzzy positive-ideal solution (FPIS, F^*) and a fuzzy negative-ideal solution (FNIS, F^-) as:

$$F^* = 1 \quad \text{and} \quad F^- = 0.$$

The distance between F_i and F^* is called positive distance, and the distance between F_i and F^- is called negative distance. The two kinds of distances are calculated by $d_i^* = d(F_i, F^*)$ and $d_i^- = d(F_i, F^-)$ respectively, where $d(\cdot)$ is the quasi-distance of two finite fuzzy numbers.

Step 10: Calculate the closeness coefficients.

Then, to determine the ranking order of all candidate sites, a closeness coefficient is defined as:

$$CC_i = \frac{1}{2}(d_i^- + (1 - d_i^*)), \quad i = 1,\ldots,m, \tag{5}$$

4. A case study on Taobao.com

4.1. Identification of candidate sites

The process of identification of candidate sites is composed of five steps on three levels.

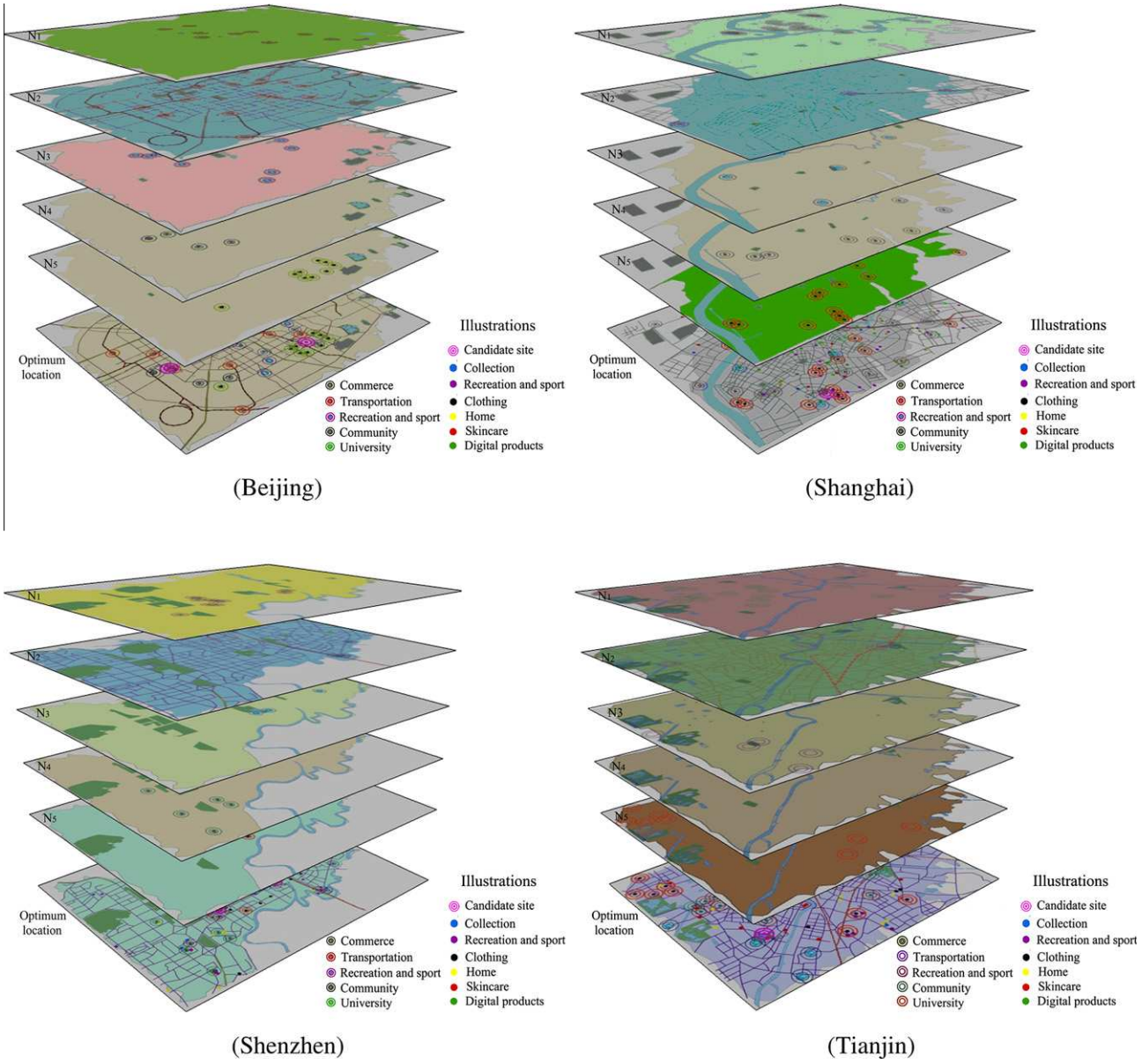


Fig. 1. Distribution of fuzzy location choice and candidate sites of location optimization for online shops of digital products in Beijing, Shanghai, Shenzhen, and Tianjin.

Level one: Object selection (Step1).

Step 1: Obtaining online shop samples and their locations.

As the largest eBay-like online shopping website in China, Taobao.com was selected. Nearly 80% C2C business were done by it in China. Therefore, it is representative to take Taobao.com to study. The samples in this study only include diamond level (premium membership) online shops on Taobao.com. The four main cities, Shanghai, Beijing, Shenzhen, and Tianjin, in China were selected to study, and location data of online shops was got by using the advanced search function in Taobao.com.

Level two: Condition definition (Steps 2–4).

Step 2: Defining the goods categories.

There are nine goods categories listed on Taobao.com, including virtual, digital products, home, collection, clothing, skincare, recreation and sports, auction and others, and many sub-classifications under each category. According to the goods characteristics of virtual, auction and others mentioned above, only six goods categories on Taobao.com were taken as study objects of online shops. Comparing with other general goods, the digital products[1] present obvious location choice characteristics, so we took digital products as the example for the study on location choice and optimization problem.

Step 3: Defining neighborhood infrastructure.

Based on the influence factors of online shops' location choice, five neighborhood infrastructures, commercial area (N_1), transportation center (N_2), recreation and sports stadiums (N_3), large living community (N_4), and university (N_5) were selected. Using five neighborhood infrastructures labeled on the maps of four sample cities which are published by China Map Publishing House, the number of neighborhood infrastructures in each city was identified by transverse comparison. 55 neighborhood infrastructures were se-

[1] Digital products: mobile phone/NOKIA/Samsung, laptop/ThinkPad/DELL, computer hardware/LCD/desktop complete computer/internet, digital camera/video camera/graphic printing, MP3/MP4/MP5/iPod/recorder pen, flash memory/USB Disk/memory stick/removable storage, accessories for mobile phone/camera/digital products, office installation/stationery/expendable, household electric appliance/video and audio HiFi/living/kitchen electricity.

Table 4
Number and ratio of online shops of digital products in different location types of Beijing, Shanghai, Shenzhen, and Tianjin.

Location	Complete location	Overlap location	Transitional location	Incomplete location
Cities	Number/ratio			
Beijing	3/9.1	20/60.6	1/3.00	9/27.3
Shanghai	38/40.4	5/5.3	25/26.6	26/27.6
Shenzhen	42/82.4	6/11.76	2/3.92	1/1.96
Tianjin	0/0	36/92.31	0/0	3/7. 69

lected in Beijing, 71 in Shanghai, 42 in Tianjin, and 34 in Shenzhen.

Step 4: Classification of location types.

Based on the definitions of complete location, overlap location, transitional location, and incomplete location, the location types of online shops of digital products can be classified.

Level three: Provide candidate sites (Step 5).

Step 5: Identification of candidate sites.

By using fuzzy location choice method mentioned above, the number and ratio of online shops of digital products falling into different location types can be got, in which the online shops are based on neighborhood infrastructures (see Table 4). By marking the online shops' positions on the maps of different neighborhood infrastructures under the condition of neighborhood infrastructure coordinate point and segmental region, the distribution map of online shops of digital products was generated. Comparing with scattered distribution, some online shops of digital products have distinctly regional centralization phenomenon. These sites can be selected as candidate sites of optimum location, and totally 16 were selected. The distribution map of candidate sites for location optimization was then generated by integrating different layers (see Fig. 1).

The online shop location choice characteristics of digital products relatively meet traditional Ghana model, and the online shops of digital products tend to distribute in a cluster to generate scale merit. Therefore, it has distinct location selection. The ratio of complete or overlap location for digital products is the highest among the six goods categories of online shops mentioned above. Overlap location of Tianjin occupies 92.3%, complete location of Shenzhen takes 82.4%, and overlap location of Beijing is 60.61%. It is suggest that influenced by one or more neighborhood infrastructures, most online shops of digital products are highly centralized. Detailed descriptions are as follows: Shenzhen online shops of digital products centralize in North Huaqiang Digital Mart; Tianjin online shops of digital products centralize in Yigao Digital Square in Baidi Road of Nankai District, Modern Digital Square in Anshan West Street of Nankai District, Hechuan Building in Nanjing Road of Heping District, and Taige Communication City at the cross of Weijin Road and Xinxing Road of Nankai District; Beijing online shops of digital products centralize in Nanxi Building of Muxiyuan, Zhongguancun Street, and around Zhongguancun Silicon Valley Computer City. Hence, the shops gather in digital plaza or commercial buildings, and location choice tends to be affected by traditional factors. This may attribute to the substance of valuable products themselves. The threshold of this kind of plaza is relatively high, so trust of shop has become the main factor. At the same time, near to high-tech and specialized labor and new intellectual areas are also important factors, which meets Schriner's estimate. The following will analyze location optimization for the online shops of digital products.

4.2. Calculation of location optimization

The calculation process is composed of 10 steps on three levels:

Level one: Determine the expression and weights of evaluation aspects and experts (Steps 1–3).

Step 1: Determine the expression of experts and evaluation aspects.

Table 5
Impact weights of neighborhood infrastructure on candidate sites.

Neighborhood infrastructure	Expert 1	Expert 2
Commerce	*Absolutely important*	*Strongly important*
Transportation	*Absolutely important*	*Absolutely important*
Recreation and sports	*More important*	*More important*
Community	*More important*	*Important*
University	*Important*	*Less important*

Two experts, Expert 1 and Expert 2, are introduced in this study. Sixteen selected candidate sites from four cities are illustrated in Table 6. Five neighborhood infrastructures illustrated in Table 4 are chosen as evaluation criteria.

Step 2: Determine weights of evaluation aspects/criteria.

Two experts make impact weights of five neighborhood infrastructures on candidate sites as shown in Table 5.

Step 3: Determine weights (importance degrees) of experts.

Both of the two experts are weighted as *Most important*.

Level two: Individual preference generation (Steps 4–6).

Step 4: Set up the relevance degree (rating scores) of each candidate site on each criterion.

In this research, two experts give the importance rating S_{itj} of the five neighborhood infrastructures towards 16 candidate sites according to their experience and preference, as shown in Table 6.

Step 5: Calculate the fuzzy appropriateness indices of all the candidate sites.

The fuzzy appropriateness index of candidate site A_i according to expert E_j, F_{ij} is calculated by using

$$F_{ij} = \sum_{t=1}^{5} W_{tj} \times S_{itj}, \quad i = 1, \ldots, 16; \ j = 1, 2, \tag{1}$$

Step 6: Normalize the fuzzy appropriateness indices.

F_{ij}, $i = 1, \ldots, 16$; $j = 1, 2$, are normalized by

$$\overline{F}_{ij} = \frac{F_{ij}}{\sum_{s=1}^{16} F_{sj_0}^R}, \quad i = 1, \ldots, 16; \ j = 1, 2, \tag{2}$$

Level three: Group aggregation for final ranking (Steps 7–10).

Step 7: Normalize the weights of experts.

Each expert E_j has been assigned a weight v_j, $j = 1, 2$. The normalized weight of E_j is denoted as

$$\bar{v}_j = \frac{v_j}{\sum_{s=1}^{2} v_{s_0}^R}, \quad j = 1, 2, \tag{3}$$

Step 8: Calculate normalized weighted fuzzy appropriateness indices of candidate sites

The final fuzzy appropriateness index of candidate site A_i aggregating all experts' opinions, F_i is computed by

$$F_i = \sum_{j=1}^{2} \bar{v}_j \times \overline{F}_{ij}, \quad i = 1, \ldots, 16, \tag{4}$$

Step 9: Calculate distances between normalized weighted fuzzy appropriateness indices and the positive-ideal and the negative-ideal values, respectively.

Table 6
Evaluation of the importance rating of neighborhood infrastructure towards candidate sites.

	Candidate sites	Expert	Commerce	Transportation	Recreation & sports	Community	University
Beijing	1	1	Very good	Very good	Very good	Very good	Absolutely good
		2	Very good	Very good	Very good	Very good	Absolutely good
	2	1	Absolutely good	Very good	Fair	Very poor	Very poor
		2	Very good	Very good	Good	Poor	Very poor
	3	1	Good	Very good	Absolutely good	Poor	Absolutely poor
		2	Very good	Very good	Very good	Absolutely poor	Poor
	4	1	Absolutely good	Absolutely good	Fair	Poor	Very poor
		2	Very good	Absolutely good	Fair	Poor	Very poor
	5	1	Absolutely good	Very good	Good	Very poor	Very poor
		2	Very good	Very good	Very good	Poor	Very poor
Shanghai	1	1	Absolutely good	Absolutely good	Very good	Good	Absolutely good
		2	Absolutely good	Absolutely good	Fair	Very good	Very good
	2	1	Absolutely good	Very good	Fair	Absolutely poor	Poor
		2	Absolutely good	Very good	Good	Very poor	Very poor
	3	1	Absolutely good	Very good	Good	Very poor	Very poor
		2	Absolutely good	Very good	Fair	Poor	Absolutely poor
	4	1	Absolutely good	Absolutely good	Fair	Very poor	Absolutely poor
		2	Absolutely good	Absolutely good	Good	Absolutely poor	Very poor
	5	1	Absolutely good	Absolutely good	Absolutely good	Very good	Good
		2	Absolutely good	Very good	Good	Very good	Very good
Shenzhen	1	1	Very good	Absolutely good	Good	Good	Very poor
		2	Absolutely good	Absolutely good	Good	Fair	Very poor
	2	1	Absolutely good	Very good	Very good	Absolutely poor	Very poor
		2	Absolutely good	Absolutely good	Very good	Very poor	Absolutely poor
	3	1	Absolutely good	Very good	Good	Good	Very poor
		2	Absolutely good	Very good	Very good	Fair	Very poor
Tianjin	1	1	Very good	Absolutely good	Good	Fair	Absolutely poor
		2	Very good	Very good	Very good	Good	Very poor
	2	1	Very good	Very good	Very good	Good	Absolutely poor
		2	Absolutely good	Absolutely good	Very good	Very good	Very poor
	3	1	Absolutely good	Absolutely good	Poor	Poor	Very poor
		2	Absolutely good	Very good	Absolutely good	Very poor	Poor

Table 7
Ranking values of the fuzzy appropriateness indices for the location optimization of 16 candidate sites in Beijing, Shanghai, Shenzhen, and Tianjin.

Candidate sites	Ranking values CC_i of fuzzy appropriateness indices	Location type	Location number
Shanghai5	0.146466	Overlap location	4
Beijing1	0.145887	Overlap location	4
Shanghai1	0.144073	Overlap location	3
Tianjin2	0.130602	Overlap location	2
Shenzhen3	0.124804	Overlap location	2
Shenzhen 1	0.124006	Overlap location	2
Tianjin 1	0.121139	Overlap location	2
Shenzhen 2	0.113289	Overlap location	2
Tianjin 3	0.112743	Complete location	1
Beijing 5	0.111875	Complete location	1
Beijing 3	0.109656	Complete location	1
Beijing 4	0.109358	Complete location	1
Shanghai 4	0.106725	Complete location	1
Shanghai 3	0.106645	Complete location	1
Beijing 2	0.106088	Complete location	1
Shanghai 2	0.105888	Complete location	1

$$d_i^* = d(F_i, F^*) \quad \text{and} \quad d_i^- = d(F_i, F^-),$$

where $d(\cdot)$ is the quasi-distance of two finite fuzzy numbers.

Step 10: Calculate the closeness coefficients.

Then, to determine the ranking order of all candidate sites, a closeness coefficient is defined as:

$$CC_i = \frac{1}{2}(d_i^- + (1 - d_i^*)), \quad i = 1, \ldots, 16, \tag{5}$$

We can obtain the ranking values CC_i of the fuzzy appropriateness indices for 16 candidate sites in four cities as shown in Table 7.

From Table 7, we find that: (1) location optimization is affected by the element composition of neighborhood infrastructures. The ranking values of the fuzzy appropriateness indices for the location optimization can be expressed as a transition from the overlap location to the complete location in element composition. The impact power of the complete location depends on the weight. (2) The role of the overlap location composition consists of the following types: (a) the composition of commerce, transportation, university, recreation and sports has the strongest location impact power, such as Shanghai Pudong New District and Beijing Zhongguancun; (b) the composition of commerce, university, recreation and sports follows closely behind, as in Shanghai Xuhui District, and Tianjin Nankai District; (c) the composition of commerce and transportation also plays a major role, such as North Huaqiang and South Huaqiang of Shenzhen; (d) the composition of transportation, recreation and sports, such as Tianjin drum-tower commerce District; (e) the commerce impact power, such as, Beijing

Xidan, Shanghai Jing'an District, and Beijing Wangfujing; and (f) the transportation impact power, such as Liuliqiao and Gongzhufen area of Beijing and the railway station in Shanghai Zhabei District.

5. Conclusions

In order to understand and solve the location optimization problem of the E-service network completely, the decision-making process is divided into two stages. In the first stage, the location choice characteristics of online shops which sell digital products are defined, and the candidate sites are offered. Consideration of these candidate sites lays the groundwork for further evaluation. In the second stage, the optimum location is selected by using the FMCDM method to incorporate the information provided by two experts who fulfill the ranking of 16 candidate sites with respect to five different criteria. The result of the first stage shows that a method which takes explicit neighborhood infrastructures and location types as the criteria for defining candidate sites is feasible. The online shops selling valuable digital goods have aggregation characteristics in location choice. The overlap location ratio of these goods categories is the highest among all goods, and the location of those online shops is influenced by the city's commercial center, university, and transportation. Thus, location is still a factor in understanding the geographical phenomenon in the Internet age. The result of the second stage shows that location optimization is influenced by the element composition of neighborhood infrastructures. This kind of element composition can be expressed as a transition from the overlap location to the complete location, and the composition of the overlap location plays a major role. It includes various types of location influences from the strongest to the weakest, and the greater the number of locations, the more distinct the location choice characteristics will be.

The research findings show that fuzzy location choice method and the FMCDM method have a well-structured architecture and a great computational power. Perceiving the relationship between different objectives can help to improve the quality of decision-making under uncertainty. This study has presented further understanding of E-service network location choice. It contributes to the development of geographical location theory as being half virtual, half real in terms of theory [19] and it practically aids the solution of current problems such as excess aggregation of E-retail networks, excessively large scale of monomer, and inaccurate market positioning. Methodologically, the data processing in the first stage and the calculation in second stage are better integrated, which can perfect the application of FMCDM. We are working on a further evaluation of supply chain management at Taobao.com.

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