

A novel decision support model for satisfactory restaurants utilizing social information: A case study of TripAdvisor.com



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HIGHLIGHTS

- A novel restaurant decision support model for TripAdvisor.com is established.
- Fuzzy sets are introduced to describe tourists' review information.
- A similarity method is developed to deal with sparse data.
- Bonferroni mean are introduced to consider interdependence among criteria.
- The model is tested through a case study of TripAdvisor.com.

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ABSTRACT

Decision support models for satisfactory restaurants have attracted numerous researchers' attention. Many extant models do not consider the active, neutral and passive information in online reviews all at once. Moreover, they ignore the effect of interdependence among criteria on tourists' decision-making. To cover these defects, this study proposes a restaurant decision support model using social information for tourists on TripAdvisor.com. The model introduces fuzzy sets to denote online reviews and utilizes Bonferroni mean to consider interdependence among criteria. Furthermore, it uses a novel similarity measurement which can handle sparse data in fuzzy environments. To validate the model, we conduct a case study of TripAdvisor.com which compares the proposed model with four other models. The performance of each model is evaluated by the metric called the mean absolute error. The study shows that the proposed model can effectively support tourists' decision-making and it performs better than the other four models.

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1. Introduction

Information technology and social media have changed the way that tourists search for restaurants. Thanks to Internet, limitations on space and time for planning independent trips in advance have diminished. Consequently, tourists are able to access tourism websites to learn about cuisine in their travel destinations and find satisfactory restaurants (Rodríguez-Molina, Frías-Jamilena, & Castañeda-García, 2015). For example, a tourist living in Beijing can browse summaries of Taiwanese restaurants via TripAdvisor.com, a tourism website, before arriving in Taiwan. Furthermore, social tourism websites, like TripAdvisor.com, allow tourists to post reviews publicly online, so that other tourists can have a further knowledge of restaurants on those websites (Limberger, Dos Anjos,

de Souza Meira, & dos Anjos, 2014). For instance, a tourist might think that a certain Taiwanese restaurant will be excellent based on the introduction provided by its owner, but he or she may change his or her mind after browsing tourist reviews if most of the reviews mention that the food is anything but tasty. In summary, information technology and social media facilitate tourists' decision-making about restaurants.

However, these technological advances might lead to some negative effects (Duffy, 2015). Specifically, Internet provides tourists with countless suggestions for restaurants and information about cuisine. The great volumes of suggestions are truly valuable to tourists' restaurant decision-making, but they also increase independent tourists' difficulty in finding satisfactory restaurants. In addition, the exponential growth of online reviews posted by countless tourists on social tourism websites further augments potential tourists' obstacles to making decisions about meals (Fang, Ye, Kucukusta, & Law, 2016). For example, as Fig. 1 shows, if a tourist wants to employ TripAdvisor.com to find a satisfactory restaurant

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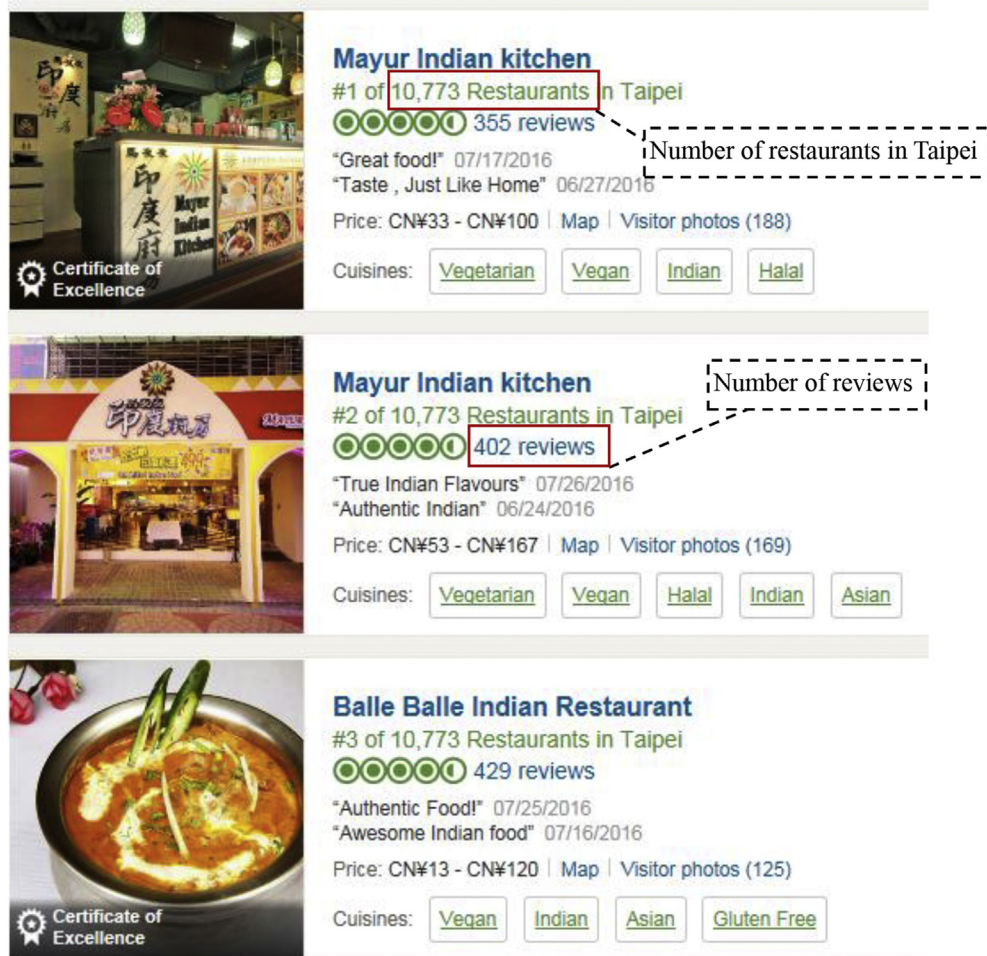


Fig. 1. A screen shot from TripAdvisor.com.

in Taipei, Taiwan, the website presents 10,274 different restaurants as options. Fig. 1 is a screen shot from TripAdvisor.com. It displays part of recommendation list of restaurants in Taipei, Taiwan. The recommendation list generated by TripAdvisor.com presents every restaurant's representative image and some basic information like its ranking, total rating, number of reviews, titles and time of the latest two reviews, average price and cuisines. In this example, more than 400 restaurants receive hundreds of reviews, and some restaurants even receive more than one thousand pieces of reviews. This information overload can make it extremely difficult for a tourist to find a satisfactory restaurant immediately. Therefore, researchers in the field of restaurant and tourism have begun to focus on constructing a decision support model to assist tourists in finding satisfactory restaurants easily, quickly and accurately (Schuckert, Liu, & Law, 2015; Thiengburanathum, Cang, & Yu, 2015). And the main purpose of this study is to establish a decision support model utilizing social information, namely the shared travel experience, to help independent tourists visiting TripAdvisor.com find satisfactory restaurants.

Numerous researchers have studied decision support models that utilize social information to influence potential tourists' decision-making about restaurants (Gretzel & Yoo, 2008), and these models have proven to be effective (Farooque, Khan, Bin Jun, & Gupta, 2014; Nilashi, Ibrahim, Ithnin, & Sarmin, 2015). Generally, social information is generated from human communication or

interaction. On social tourism websites, social information is mainly composed of online reviews and social relationships. In recent years, the influence of online reviews on decision-making has been qualitatively investigated and quantitatively applied (Cheng & Loi, 2014; Lu & Stepchenkova, 2012; Sparks, Perkins, & Buckley, 2013; Xiang & Gretzel, 2010). Moreover, many researchers have indicated that social relationships may affect the influence of online reviews on decision-making, and these researchers have therefore introduced social relationships into decision support models. Nevertheless, three defects exist in prior studies on decision support models in the restaurant and tourism industry. The first one is the incomplete utilization of online reviews. The prior models use real numbers to denote tourists' reviews resulting in the loss of fuzzy and uncertain information (Benitez, Martín, & Román, 2007; Schuckert et al., 2015). The second one lies in the quantitative method of the social relationships. The values of most prior quantitative methods, including those dealing with sparse data, range within $[-1, 1]$ (Patra, Launonen, Ollikainen, & Nandi, 2015). Those methods cannot be applied to determine the degrees of social relationships under fuzzy environments since fuzzy numbers, such as interval-valued neutrosophic numbers (IVNNs), cannot be multiplied by negative real numbers (Zhang, Ji, Wang, & Chen, 2016). The third one is that previous multi-criteria decision support models do not take into consideration interdependence among criteria (Hu, 2013). A multi-criteria decision support model, which is an

important branch of decision support models, utilizes multi-criteria online social reviews rather than the overall single-criterion online ratings used by a traditional decision support model. Extant multi-criteria models suppose that the integrated criteria are mutually independent, while they are actually interdependent.

With regard to online reviews, the vast majority of previous decision support models only make use of the numerical rating, which is a small component of the entire review. Unlike numerical ratings, text reviews can express tourists' specific and nuanced attitudes toward an item. In addition, text reviews may contain fuzzy, uncertain and imprecise information that cannot be described by numerical ratings (Li, Law, Vu, & Rong, 2013a). For instance, on TripAdvisor.com, a tourist may rate an individual restaurant's food as 4-star and its value as 3-star in a 5-star marking system, and he or she may also post a text review. The content of the text review may state that the food tasted good but not excellent, and that it was a little expensive but still worth it. As this example illustrates, text reviews explain the tourist's evaluation about the restaurant in more detail compared with numerical ratings, and numerical ratings are the overall reflection of information in text reviews. However, the extant decision support models only make use of numerical ratings without further mining and utilizing fuzzy and uncertain information in text reviews. To overcome this deficiency, fuzzy logic needs to be introduced (Jeoushyan, Liu, Shengfang, Yin, & Changyen, 2014; Wang, 2007).

The real meaning of reviews is still considered not to be described enough. As dividing reviews into active and passive ones is only around 70% accurate, the mining process returns just a collection of keywords which is far from any expected result (Schuckert et al., 2015). In fact, each individual text review may include active, neutral and passive information (Zhang et al., 2016). For example, a tourist may comment about a certain restaurant that the appetizer was delicious, the fish was neither good nor bad, and the other dishes were truly awful. The active, neutral and passive information comprised in review can be depicted utilizing the degrees of truth, neutrality and falsity in a neutrosophic set (Smarandache, 1998, 1999), which is an extension of a fuzzy set. In addition, interval numbers are preferred over specific numbers in describing uncertainty in active, neutral and passive information. Therefore, this study introduces interval-valued neutrosophic sets (IVNSs) (Wang, Smarandache, Zhang, & Sunderraman, 2005) to quantify tourist reviews.

Numerous prior studies utilized social relationships by obtaining degrees of similarity between tourists (Patra et al., 2015; Wang, Zhang, & Lu, 2015). Many works have studied similarity models, such as the cosine similarity model (Salton & McGill, 1986), the adjusted cosine similarity model (Sarwar, Karypis, Konstan, & Riedl, 2001), the Pearson correlation (PC) model (Ekstrand, Riedl, & Konstan, 2011), and the constrained PC model (Shardanand & Maes, 1995). Unlike these similarity models only considering absolute rating differences, (Wang et al., 2015) utilized the information entropy on the relative differences of items' ratings to construct a similarity model. In addition, many studies have addressed similarity measurements while dealing with sparse data (Anand & Bharadwaj, 2011; Luo, Niu, Shen, & Ullrich, 2008). In particular, a novel similarity model was developed by combining Bhattacharyya coefficient (BC) and the Jaccard similarity measurements (Patra et al., 2015). This example is relevant because data about restaurants on social tourism websites are actually sparse. In general, it is rare that two tourists go to the same restaurant for meals and then they rate the exact same restaurant on TripAdvisor.com. Furthermore, tourist reviews are quantified by IVNSs which cannot be multiplied by negative real numbers. In other words, similarity degrees between tourists should be non-negative in this study. Considering these facts, we develop a novel Bhattacharyya

similarity (BS) measurement with value ranging from zero to one. In addition, the similarity model in this study incorporates the entropy-based similarity measurement (Wang et al., 2015) with the novel BS measurement to improve the importance of the common restaurants rated by two tourists (hereafter termed co-rated restaurants).

As studied by many researchers, multiple criteria are involved in tourists' selection of restaurant. Previous researches pointed out that tourists consider not only quality of food but some other factors when selecting a restaurant. For example, some researchers thought that place and ambiance of restaurant were influential factors of tourists' restaurant decision-making besides food (Sulek & Hensley, 2004). Furthermore, good value and service were indicated to be necessary for restaurants to attract tourists by (Choi, Lee, Zhao, Choi, & Lee, 2009). Moreover, two other influential factors, including cleanliness and friendliness of staff (i.e., service), have been confirmed (Tripp, Greathouse, Shanklin, & Gregoire, 1995). (Hwang, Lee, & Park, 2012) divided the most important factors into five dimensions including food and environment, service and courtesy, price and value, location, and advertising and promotion. Moreover (Mak, Lumbers, Eves, & Chang, 2012) summarized all influential factors into six dimensions comprising sensory attributes, food content, methods of preparation and cooking, food type, food availability, and price, value and quality. Besides the above factors, some other factors may influence tourists' selection of restaurants (Chang, Kivela, & Mak, 2011; Mak et al., 2012), including tourists' own food culture, the contextual factor of the dining experience, perception of the destination and service encounter. Influential factors are also considered in practical tourism websites in the form of multiple criteria. Instead of considering all factors, most tourism websites only provide several most important influential factors for tourists to review. For instance, tourists on TripAdvisor.com can rate restaurants with respect to four criteria, including food, service, value and atmosphere.

The involved multiple criteria in tourism websites are correlative (Li et al., 2013a). For instance, the four criteria in TripAdvisor.com are interdependent. For obvious reasons, value may be affected by the other three criteria, and service may be bound up with atmosphere. However, most extant multi-criteria decision support models integrate multiple criteria using the weighted arithmetic average (WA) approach, in which the interdependence among criteria are not taken into account (Liu, Mehmandjiev, & Xu, 2011; Nilashi, bin Ibrahim, & Ithnin, 2014; Shambour & Lu, 2011). In order to overcome this deficiency, we employ the Bonferroni mean (BM) to integrate interdependent criteria in this study. BM was originally proposed by (Bonferroni, 1950) and then generalized by (Yager, 2009). It can capture the interdependence among arguments. Furthermore, previous researches have extended the use of BM to various fuzzy environments (Tian, Wang, Wang, & Chen, 2015, 2016). For instance, BM has been introduced into intuitionistic fuzzy environments (Xu & Yager, 2011), and the intuitionistic fuzzy BM (IFBM) and the weighted IFBM operators were defined. Moreover, the BM operator under single-valued neutrosophic environments was developed (Liu & Wang, 2014) and other researchers further studied BM under normal neutrosophic number environments (Liu & Li, 2015).

This study has four main purposes. The first is to establish a comprehensive decision support model for helping independent tourists to choose restaurants using social information on TripAdvisor.com. The second lies in exploring a new similarity measurement that is suitable for handling sparse data under fuzzy environments. The third is to develop a novel integration model that takes into consideration interdependence among criteria. The final purpose is to demonstrate the necessity and process of utilizing the proposed decision support model in TripAdvisor.com. The

rest of this study is organized as follows. Section 2 establishes a decision support model for TripAdvisor.com aiming at helping independent tourists find satisfactory restaurants using social information. To verify the feasibility of the model, Section 3 conducts a case study on restaurants using data from TripAdvisor.com. The results are listed and discussed in Section 4. Finally, Section 5 concludes this study and suggests several directions for future research.

2. A comprehensive decision support model using social information

As illustrated in Section 1, three deficiencies exist in the prior restaurant decision support models. To cover these shortcomings, this study establishes a comprehensive decision support model which focuses on assisting the independent tourists on TripAdvisor.com to find satisfactory restaurants in their destinations. The remainder of this section introduces the details of the novel decision support model.

2.1. Structure of the decision support model

Social information on tourism websites plays an important role in potential tourists' restaurant decision-making. As to fully describing information in online social reviews, IVNNs are more effective than specific numerical values. Moreover, data about restaurants are often sparse in practical tourism websites, and tourist reviews are written based on several correlative criteria. Based on these principles, we establish a comprehensive decision support model for TripAdvisor.com that not only makes full use of social information, including online reviews and social relationships, but also takes into consideration interdependence among criteria. This decision support model employs IVNNs to quantify online social reviews, introduces BM to aggregate criteria, and utilizes a novel similarity measurement to deal with sparse data.

The model in this study primarily consists of three modules: the transformation module, the similarity module and the integration module. The transformation module utilizes and transforms the online reviews into IVNNs to depict the fuzzy and uncertain information in reviews. The similarity module mines and utilizes social relationships by calculating the degrees of similarity between tourists. The integration module takes into account the interdependence among criteria by introducing BM operators.

For the sake of clarity, Fig. 2 depicts the structure of the proposed decision support model. More details of this novel model are explained throughout the rest of this section.

For ease of description, in this study we use v_t to represent one of the T similar tourists of the target tourist group u . The ratings of tourist v_t about restaurant i are under n criteria (c_1, c_2, \dots, c_n) and the collection of these ratings can be written as $\{r_{v_t i}^1, r_{v_t i}^2, \dots, r_{v_t i}^n\}$. Furthermore, the weight vector $W = (w_1, w_2, \dots, w_n)^T$ depicts the

importance of every criterion for the target tourist u .

2.2. Transformation module

As described in Section 1, a rating in the form of an IVNN can depict active, passive and neutral information, as well as fuzziness and uncertainty, all of which are simultaneously contained in a tourist's restaurant review and overall reflected by the tourist's numerical ratings. A rating in the form of a numerical or linguistic value cannot offer the same descriptive breadth. Based on this viewpoint, our study characterizes every tourist's review under each criterion by an IVNN, which is an element of an IVNS, as $\langle [A^-, A^+], [N^-, N^+], [P^-, P^+] \rangle$. A rating expressed by an IVNN is hereafter called an IVNN rating. In this way, our study takes advantage of information in reviews to the most extent. The interval value $[A^-, A^+]$ quantifies the active information, the interval value $[N^-, N^+]$ quantifies the neutral information, and the interval value $[P^-, P^+]$ quantifies the passive information. The emphasis of our study is the idea of utilizing IVNNs to denote active, passive and neutral information all at once other than the technology of transformation. Therefore, we do not introduce the detailed technologies and procedure of the transformation but explain the principles the transformation follows.

The thinking of analyzing text reviews is as follows. It is necessary to build an emotion dictionary including the active, neutral and passive emotional words. Please refer to (Bracewell, 2008; Rao, Lei, Wenying, Li, & Chen, 2014) for the details of the construction of the emotion dictionary. Then the active, neutral and passive degrees of a text review should be determined utilizing sentiment analysis technologies based on its wording (such as very good, good, not bad, and bad) and the degrees of certainty, uncertainty and hesitancy under each criterion (such as absolutely, maybe, and a little bit). Please refer to (Agarwal, Poria, Mittal, Gelbukh, & Hussain, 2015; Xia, Cambria, Hussain, & Zhao, 2015) for the details of the sentiment analysis technologies. The purpose of introducing IVNNs to denote text reviews is to mine and utilize information as much as possible, and improve the performance of decision support model. If a text review includes active, neutral and passive information, IVNNs can be obtained by mining the text review. If a text review is too short to include active, neutral and passive information all at once, it is unnecessary to mine and utilize the text review, and numerical ratings can be used. As illustrated in Section 1, the numerical rating reflects the information in the text review to some extent. IVNNs transformed from numerical ratings partly depict the latent active, neutral and passive information.

2.3. The similarity module

Previous studies have proven that tourists who share similar preferences or behaviors tend to be interested in the same restaurants (De Meo, Nocera, Terracina, & Ursino, 2011). Based on this

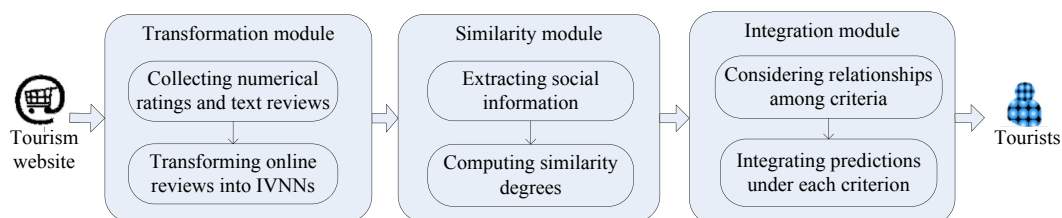


Fig. 2. The structure of the proposed decision support model for restaurants.

finding, it is reasonable to predict the target tourist's ratings based on similar tourists' ratings. In order to do that, the main challenge is to develop a measurement that can yield the degrees of similarity between tourists. However, data are often sparse in practical social tourism websites. It is therefore necessary for the similarity measurement to be capable of dealing with sparse data.

As illustrated by (Wang et al., 2015), similarities between tourists can be obtained through information entropy. Our study obtains the degree of entropy-driven similarity between tourists based on the following entropy-driven user similarity measurement (Wang et al., 2015):

$$\begin{aligned} \text{sim}(u, v_t)^{\text{Entropy}} &= 1 - \frac{H}{\log_2 N} \\ &= 1 - \left| \sum_{i=1}^N \left(-\frac{\Delta d_i}{\Delta d} \log_2 \frac{\Delta d_i}{\Delta d} \right) \right| / \log_2 N, \end{aligned} \quad (1)$$

$$\Delta d_i = |(r_{ui} - \bar{r}_u) - (r_{v_i} - \bar{r}_{v_t})|, \quad (2)$$

$$\Delta d = \sum_{i=1}^N \Delta d_i, \quad (3)$$

where N is the number of co-rated restaurants between tourists u and v_t , r_{ui} is tourist u 's rating of restaurant i , r_{v_i} is the rating made by the similar tourist v_t of restaurant i , and \bar{r}_u and \bar{r}_{v_t} are the average values of ratings made by tourist u and v_t , respectively. H in Equation (1) is called as the information entropy. If $\Delta d_i = 0$, $\frac{\Delta d_i}{\Delta d} \log_2 \frac{\Delta d_i}{\Delta d} = 0$. However, the entropy-driven similarity measurement requires that two tourists have already rated the same restaurants. Considering the sparsity of data, two tourists may not have rated any restaurant in common, making the entropy-driven user similarity measurement unsuitable. To overcome this deficiency, we combine the entropy-driven user similarity measurement with the BC measurement (Patra et al., 2015), which can solve the sparse data problem.

The value of the BC measurement in (Patra et al., 2015) may be negative. Nevertheless, the nature of IVNNs requires that they can only be multiplied by non-negative numbers, which means that the BC measurement is not suited to deal with IVNN ratings. In order to overcome this drawback, a new BS measurement with a non-negative value is defined on the basis of the BC measurement as follows:

$$\text{sim}(u, v_t)^{\text{BS}} = \sum_{i \in I_u} \sum_{q \in I_{v_t}} BC(i, q) \text{loc}_{\text{new}}(r_{ui}, r_{v_tq}), \quad (4)$$

$$\text{loc}_{\text{new}}(r_{ui}, r_{v_tq}) = \frac{(r_{ui})(r_{v_tq})}{\sqrt{\left(\sum_{i=1}^{I_u} r_{ui}^2\right) \left(\sum_{q=1}^{I_{v_t}} r_{v_tq}^2\right)}}, \quad (5)$$

$$BC(i, q) = BC(\hat{p}_i, \hat{p}_q) = \sum_{h=1}^m \sqrt{(\hat{p}_{ih})(\hat{p}_{qh})}, \quad (6)$$

where $BC(i, q)$ is the BC between restaurants i and q , $\text{loc}_{\text{new}}(r_{ui}, r_{v_tq})$ is the local similarity, m represents the number of grading levels, $\hat{p}_{ih} = \frac{\#h}{\#i}$, $\#h$ is the number of tourists who have rated restaurant i with rating h , $\#i$ is the total number of tourists who have rated restaurant i , r_{ui} denotes the rating of restaurant i by tourist u , I_u and I_{v_t} are two collections of items rated by the target tourist u and similar tourist v_t , respectively.

Based on the entropy-driven similarity measurement and the new BS measurement, our study's final similarity measurement, hereafter termed the proposed similarity measurement, is

constructed as follows:

$$\text{sim}(u, v_t) = \frac{\text{sim}(u, v_t)^{\text{BS}} + \text{sim}(u, v_t)^{\text{Entropy}}}{2}. \quad (7)$$

If no co-rated restaurant between tourists u and v_t exists, we specify that $\text{sim}(u, v_t)^{\text{Entropy}} = 0$. This similarity measurement, which makes use of tourists' numerical ratings, is suitable for situations where the intersection of restaurants rated by two tourists is empty.

2.4. The integration module

Since ratings are provided under n criteria, the overall prediction is obtained by integrating predictions under every criterion. Considering the interdependence among criteria, we introduce two extensions of BM to obtain the overall prediction value r_i . These two extensions are the interval-valued neutrosophic weighted Bonferroni mean (IVNWBM) and the interval-valued neutrosophic weighted geometric Bonferroni mean (IVNWGBM).

Let pred_i^j ($j = 1, 2, \dots, n$) be a collection of predictions under each criterion c_j about restaurant i . The overall prediction rating r_i can be obtained by aggregating all pred_i^j with the IVNWBM or IVNWGBM operators. The formulae of the IVNWBM and the IVNWGBM operators are provided in Appendix A. The overall prediction rating r_i takes into account the interdependence among criteria, and is closer to the preference of tourist u than those with traditional integration operators like the WA.

2.5. The process of the model

As discussed in Section 1, tourism websites usually ask a tourist to rate a restaurant according to several criteria. These multi-criteria ratings provide more information than single-criterion numerical ratings. Furthermore, it has been proven that the multi-criteria decision support model generally improves the accuracy of predictions compared with models that utilize corresponding single-criterion ratings (Liu et al., 2011). On the basis of

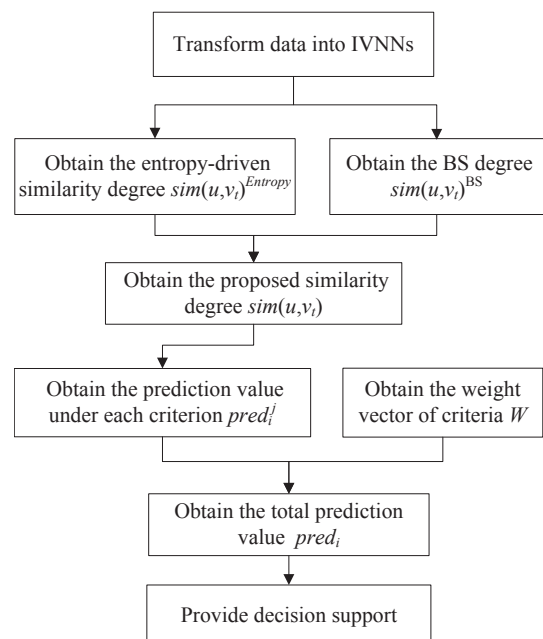


Fig. 3. The process of the restaurant decision support model.

these statements, we construct a multi-criteria decision support model utilizing the similarity measurement in Subsection 2.3 and the integration functions in Subsection 2.4. The process of the proposed restaurant decision support model for [TripAdvisor.com](#) includes the following steps, as illustrated in Fig. 3. Additionally, we present the algorithm of the decision support model, which can be applied in [TripAdvisor.com](#) to construct its decision support system, in Appendix B.

Step 1: Transform data into IVNNs.

The first step is to transform the collected data into IVNNs. Here, for the sake of simplicity, we make use of numerical ratings to obtain IVNNs for the purpose of mining and utilizing online reviews as much as possible. The transformation between numerical ratings and IVNNs are listed as Table 1.

Step 2: Obtain the entropy-driven similarity degree $\text{sim}(u, v_t)^{\text{Entropy}}$.

The second step is to obtain the entropy-driven similarity degree between the target tourist u and each of his or her similar tourists according to Equations (1)–(3).

Step 3: Obtain the BS degree $\text{sim}(u, v_t)^{\text{BS}}$.

The third step is to obtain the BS degree between the target tourist u and each of his or her similar tourists utilizing Equations (4)–(6).

Step 4: Obtain the proposed similarity degree $\text{sim}(u, v_t)$.

The fourth step is to obtain the proposed similarity degree between the target tourist u and each of his or her similar tourists according to Equation (7). The similarity degree is the linear combination of the entropy-based similarity and BS degree.

Step 5: Obtain the prediction value pred_i^j of the rating of the target tourist u about the target restaurant i under each criterion.

This model considers multi-criteria tourist ratings. Prediction of the target tourist's rating under each criterion should be calculated before the total prediction is obtained. Furthermore, the greater the similarity degree between the target tourist and the similar tourist, the closer their ratings of the target restaurant (Liu et al., 2011). Therefore, the prediction of the target tourist's rating of the target restaurant i under criterion c_j can be determined according to the following equation:

$$\text{pred}_i^j = \frac{\sum_{t=1}^T \text{sim}(u, v_t) \times r_{v_t i}^j}{\sum_{t=1}^T \text{sim}(u, v_t)}, \quad (8)$$

where T denotes the number of tourists similar to the target tourist

u , and $r_{v_t i}^j$ is the rating of restaurant i provided by similar tourist v_t under criterion c_j . $\text{sim}(u, v_t)$ represents the proposed similarity degree between u and v_t .

Step 6: Obtain the weight vector of criteria W .

A tourist's personalized weight vector plays a significant role in the decision support model. Based on collected total ratings and ratings under each criterion, SPSS software uses regression analysis to obtain the weight vector of the target tourist u across the integration operator, either the weighted BM (WBM) or weighted geometric BM (WGBM).

Step 7: Obtain the total prediction value pred_i .

The total prediction value of the target tourist's rating of the target restaurant i can be found by integrating predictions under every criterion $\{\text{pred}_i^1, \text{pred}_i^2, \dots, \text{pred}_i^n\}$ with the IVNWBM in Equation (A1) or IVNWGBM in Equation (A2) in Appendix A. These two integration operators take into account interdependence among criteria.

Step 8: Provide decision support for the target tourist.

The last step is ranking the alternative restaurants according to their total prediction values. The higher the total prediction value of a restaurant is, the more likely the target tourist will satisfy the restaurant. [TripAdvisor.com](#) can provide decision support for the target tourist by recommending his or her top N restaurants.

3. A case study of TripAdvisor.com

TripAdvisor.com is one of the world's leading tourism communities and it has covered restaurants in more than 190 countries, with over 200 million ratings and reviews generated by global tourists. As an American tourism website, [TripAdvisor.com](#) provides reviews and opinions of travel-related content, such as hotels, restaurants and attractions. That is to say, the target population can be identified as independent tourists. Generally, few local consumers will employ [TripAdvisor.com](#) to find restaurants rather than localized catering service platforms (like Yelp). Consequently, [TripAdvisor.com](#) does not further distinguish the independent tourists and the local consumers when recommending restaurants. In addition, as remarked above, the proposed model purposes to help tourists on [TripAdvisor.com](#) find satisfactory restaurants in their destinations. Therefore, as with [TripAdvisor.com](#), this case study is conducted without differentiating these two kinds of users, and "tourist" refers to arbitrary website user on [TripAdvisor.com](#). Moreover, [TripAdvisor.com](#) allows tourists to rate restaurants in a 5-star marking system from four separate aspects: food, service, value and atmosphere. These four criteria do have been proven to be able to influence tourists' restaurant decision-making (Heung, 2002). The current decision support model in [TripAdvisor.com](#) provides the same ranking of restaurants to all tourists without taking into account individual personalization. Fig. 1 displays part of the ranking order of restaurants in Taipei, Taiwan, given by the decision support model in [TripAdvisor.com](#). The order is produced based on the popularity degree, which depends on the numbers of tourist reviews, the values of ratings, and the update frequency of reviews, to name a few factors. Unlike the existing decision support model in [TripAdvisor.com](#), the proposed decision support model takes personalization into account by employing the personalized weights of criteria and the similarity degrees between the target tourist and other tourists.

To verify the performance of the proposed decision support

Table 1
The transformation between numerical ratings and IVNNs.

Numerical ratings	IVNNs
5 in a 5-star marking system	$\langle [0.9, 1], [0, 0.1], [0, 0.1] \rangle$
4 in a 5-star marking system	$\langle [0.75, 0.85], [0.05, 0.15], [0.15, 0.25] \rangle$
3 in a 5-star marking system	$\langle [0.55, 0.65], [0.15, 0.25], [0.35, 0.45] \rangle$
2 in a 5-star marking system	$\langle [0.35, 0.45], [0.25, 0.35], [0.55, 0.65] \rangle$
1 in a 5-star marking system	$\langle [0.15, 0.25], [0.35, 0.45], [0.75, 0.85] \rangle$

model, we conduct a case study in which the proposed model is compared with four benchmark models, using restaurant data from TripAdvisor.com. The details of the case study are discussed in the remainder of this section.

3.1. The dataset

Our dataset, which is manually collected from TripAdvisor.com, includes 14,562 records related to 451 tourists and 4820 restaurants. Among which, there are 412 records concerned the total ratings and the ratings under the four criteria provided by the tourist whose username is TrevorHall. Fig. 4 lists a part of the collected records about TrevorHall and Fig. 5 shows an example of reviews given by TrevorHall on TripAdvisor.com. As shown in Fig. 4, the first column of the records is the restaurant names marked in Fig. 5. The next five columns are the total ratings and the ratings of the four criteria (i.e., food, service, value and atmosphere) collected from the data in Fig. 5. The last column is the numbers of reviews a certain restaurant received. In addition, the dataset also contains the rating distribution of each referred restaurant. Fig. 6 presents the distributions of the total ratings that some restaurants received. The first column of the records is the restaurant names, the second column is the average ratings of all total ratings an individual restaurant received, and the last five columns are the numbers of tourists who reviewed the overall rating of a certain restaurant as 5, 4, 3, 2 and 1, respectively. We select 90% of the data as the training dataset, which includes 450 tourists' review information and records describing relative restaurants' distributions of ratings. Each tourist's review information consists of the total ratings, the ratings under each of the four criteria about all restaurants that he or she has rated. After training the proposed model and the other four models with the training dataset, we evaluate them with the rest 10% data in the test dataset which contains records of 18 similar restaurants' total ratings and ratings concerning each criterion rated by TrevorHall. Furthermore, each restaurant's distribution ratio of total ratings in our dataset agrees with its distribution ratio of total ratings on TripAdvisor.com. Fig. 7 depicts the distribution of the total ratings recorded in our dataset, including but not limited to the collected total ratings of the 18 target restaurants. The mean value of the total ratings is 4.067, and the standard deviation is 1.089.

3.2. Methodology

In order to verify the feasibility of our proposed model, we compare it with four other models. Every model is utilized to

predict ratings of TrevorHall about 18 restaurants in the test dataset. Below are the label descriptions we use to denote each of these models:

- Entropy model (Wang et al., 2015): A traditional single-criterion model in which ratings are in the form of real data, and the similarity measurement used is the entropy-based similarity measurement.
- Real data model (denoted as CFWA model): A multi-criteria model in which ratings are in the form of real data, the similarity measurement used is the proposed similarity measurement, and the criteria integration utilizes the WA operator.
- IVNN WA model (denoted as IVNNWA model): A multi-criteria model in which ratings are IVNN ratings, the similarity measurement used is the proposed similarity measurement, and the criteria integration utilizes the WA operator.
- Entropy BM model (denoted as IVNWBES model): A multi-criteria model in which ratings are IVNN ratings, the similarity measurement used is the entropy-driven similarity measurement, and the criteria integration utilizes the IVNWBm.
- The first form of the proposed model (written as IVNWB model): A multi-criteria model in which ratings are IVNN ratings, the similarity measurement used is the proposed similarity measurement, and the criteria integration utilizes the IVNWBm.
- The second form of the proposed model (written as IVNWGB model): A multi-criteria model in which ratings are IVNN ratings, the similarity measurement used is the proposed similarity measurement, and the criteria integration utilizes the IVNWGBm.

The benefits of utilizing multi-criteria ratings and the proposed similarity measurement can be shown by comparing the performance of the entropy model and the CFWA model. Moreover, comparing the performance of the CFWA model and the IVNNWA model can demonstrate the benefit of utilizing IVNN ratings. Comparing the performance of the IVNNWA model and the IVNWBES model can demonstrate whether it is necessary to consider the interdependence among criteria. Finally, comparing the performance of the IVNWBES model and the two proposed models can demonstrate the benefit of the proposed similarity measurement.

In this case study, the multiple criteria involved in the last five

A	B	C	D	E	F	G
name	overall_rating	food_rating	service_rating	value_rating	atmosphere_rating	review_number
The Stonebrook	5	4	5	5	3	158
Longsands Fish Kitchen	5	5	5	5	5	8
Skipworth Arms	1	3.5	1	1	3	13
Gigino	5	5	5	3	4.5	162
The Palm-NYC Too	5	5	5	5	4	204
Cipriani Dolci	4	3.5	4	2	5	45
City Lobster & Steakhouse	5	5	5	5	4	508
Club A Sreakhouse	2	2	2	1	4.5	2035
Crown Café	3	3	2	2	3	30
Dirt Candy	5	5	4	4	4	107
Inatteso Café	5	5	5	5	4.5	26
Ca'puccino-Heathrow Terminal	5	5	5	4	1.5	33
Winteringham Fields	5	5	5	5	4.5	409
Lilly's Tea Room	5	5	5	5	4.5	128
Steels CornerHouse Restaurant	2	4.5	1	4.5	4	576

Fig. 4. A part of records about TrevorHall.

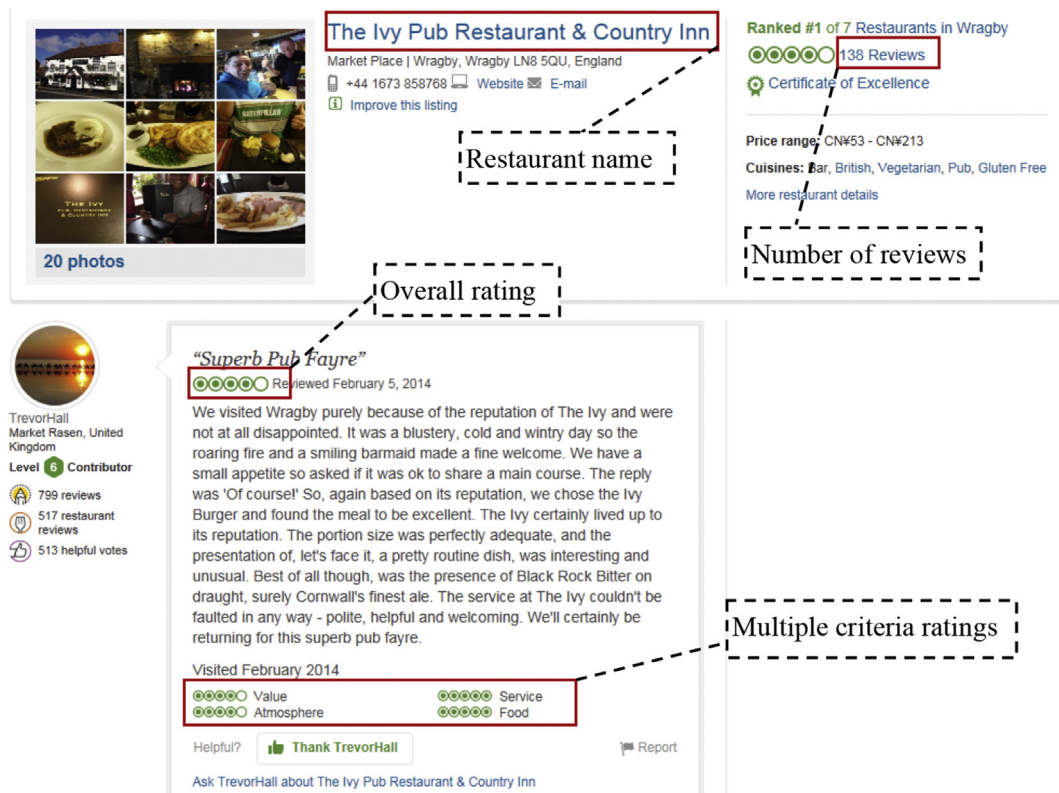


Fig. 5. An example of reviews given by TrevorHall on TripAdvisor.com.

A	B	C	D	E	F	G
name	overall_ratin	five star	four star	three star	two star	one star
The Stonebrook	5	17	42	35	26	42
Longsands Fish Kitch	5	31	3	4	1	4
Skipworth Arms	1	2	4	1	3	6
Gingino	5	68	71	21	4	4
The Palm-NYC Too	5	111	55	24	12	7
Cipriani Dolci	4	15	19	7	3	3
City Lobster & Steak	5	211	185	67	34	22
Club A Sreakhouse	2	1616	283	116	41	20
Crown Caf�	3	6	9	11	2	4
Dirt Candy	5	71	23	12	1	2
Inatteso Caf�	5	12	11	2	1	0

Fig. 6. The distributions of the total ratings that a part of restaurants received.

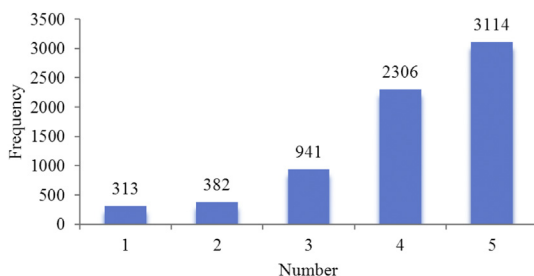


Fig. 7. The distribution of the total ratings in the dataset.

models are the four criteria used on TripAdvisor.com. As mentioned in Section 1, other influential factors (such as image and advertising) exist regarding potential tourists' restaurant decision-making (Heung, 2002; Horng, Chou, Liu, & Tsai, 2013) besides the four factors used on TripAdvisor.com. Predicting potential tourists' decisions for restaurants may be more accurate if all of these influential factors are taken into account, rather than considering only four. However, the proposed model is established with the aim of improving the extant decision support model in TripAdvisor.com. Consequently, this case study utilizes the four criteria used on TripAdvisor.com to verify the proposed model. In addition, it may be too costly to mine information about other influential factors which are barely included in most reviews on TripAdvisor.com. Moreover, all six models in this case study utilize the same criteria,

The last two models, i.e., the two forms of the proposed model, consider the interdependence among criteria. In this case study, the interdependence among the four criteria are analyzed with the Pearson correlation coefficient method and two-sided test using SPSS software. As (Li, Wu, & Lai, 2013b) pointed out, the importance of each criterion varies with each tourist, and tourists' personalized weight vectors contribute to improving the performance of decision support models. As mentioned in Subsection 3.1, we record not only TrevorHall's ratings under each of the four criteria, but also his total ratings of restaurants. Based on these data, we use SPSS software with regression analysis to obtain the weight vectors of criteria for TrevorHall using different integration functions. We also use MATLAB software to implement the six decision support models.

The closer the predictions obtained by a certain model to the actual ratings, the better the decision support model performs. Based on this understanding, we choose an evaluating metric called the mean absolute error (MAE) to evaluate the performance of the decision support models. MAE is one of the most commonly used evaluating metrics. It assesses the accuracy of a decision support model by the average absolute deviation between predictions and the target tourist's real ratings (Liu et al., 2011). The MAE equation is defined as follows:

However, the MAE formula is not suitable for models with IVNN ratings, since IVNNs do not allow subtraction operation. In order to overcome this deficiency, we propose another metric, MAE_IVNN, based on the main idea of MAE, which utilizes the average distance between predictions and the real ratings of target tourist to represent the accuracy of a decision support model:

$$d_{INN}(B, C) = \frac{1}{6} \left[\left| A_B^- - A_C^- \right| + \left| A_B^+ - A_C^+ \right| + \left| N_B^- - N_C^- \right| \right. \\ \left. + \left| N_B^+ - N_C^+ \right| + \left| P_B^- - P_C^- \right| + \left| P_B^+ - P_C^+ \right| \right].$$

4.1. Results

	Food	Service	Value	Atmosphere
Food	1	0.417**	0.445**	0.291**
Service		1	0.450**	0.445**
Value			1	0.238**
Atmosphere				1

As Table 3 and Fig. 9 show, the numbers of co-rated restaurants between TrevorHall and the majority of the 450 tourists are zero, and any number that exceeds zero is too small to be applied to accurately obtain tourist similarity. TrevorHall has one co-rated restaurant with 93 of the 450 tourists, two co-rated restaurants with 37 tourists, three co-rated restaurants with 20 tourists, and more than three co-rated restaurants with only 7 tourists. In other words, data in the dataset are sparse, and it is impossible to obtain similarity degrees accurately using traditional similarity

A	B	C	D	E	F	G
	food_active		food_neutral		food_passive	
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.9	1	0	0.1	0	0.1
	0.75	0.85	0.05	0.15	0.15	0.25
	0.75	0.85	0.05	0.15	0.15	0.25
	0.75	0.85	0.05	0.15	0.15	0.25
	0.75	0.85	0.05	0.15	0.15	0.25
	0.9	1	0	0.1	0	0.1
	0.55	0.65	0.15	0.25	0.35	0.45
	0.55	0.65	0.15	0.25	0.35	0.45
	0.15	0.25	0.3	0.4	0.75	0.85
	0.15	0.25	0.3	0.4	0.75	0.85
	0.75	0.85	0.05	0.15	0.15	0.25

Fig. 8. An example of the transformed IVNN ratings of a restaurant.

Table 3
The numbers of co-rated restaurants.

Consumer(th)	Restaurant(th)																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	3	0	0	0	2	0	0	0	2	0	1	1	0	2	0	0	0	0
2	0	1	0	0	0	0	1	0	2	0	0	0	0	0	1	0	3	0
3	1	1	0	0	0	1	0	0	0	0	3	0	0	0	1	0	0	0
4	0	0	0	0	0	0	0	0	2	0	0	0	0	2	0	0	1	0
5	0	0	0	0	0	0	0	1	1	0	1	0	0	1	2	1	1	1
6	0	0	3	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0
7	0	0	0	0	3	0	0	0	0	2	5	0	0	0	0	1	0	0
8	2	1	0	0	2	0	0	2	1	0	0	0	0	0	0	0	1	2
9	0	1	0	0	11	0	0	0	0	1	1	0	0	0	2	0	3	0
10	0	0	0	0	2	0	0	1	0	2	0	0	0	0	0	3	0	1
11	0	0	0	0	0	0	0	2	1	0	0	0	0	1	0	0	2	2
12	0	0	0	0	3	0	0	2	2	0	1	0	0	0	2	0	4	2
13	0	0	0	0	0	1	0	1	1	0	0	0	0	1	0	0	1	1
14	3	0	0	0	0	1	0	3	1	0	1	1	1	1	1	0	0	3
15	0	0	0	0	0	0	0	1	1	0	2	0	0	1	6	0	1	1
16	0	0	0	0	2	2	0	0	3	2	0	0	0	0	4	0	2	0
17	1	1	2	0	1	1	0	1	0	0	2	0	0	0	0	0	0	1
18	0	0	1	0	0	1	0	0	1	0	1	0	1	1	0	0	0	0
19	0	0	0	1	0	0	0	0	0	1	0	0	0	1	1	0	0	0
20	1	0	0	0	1	0	0	2	1	0	0	0	1	0	5	0	1	2
21	2	1	0	0	1	0	0	1	0	1	1	0	0	2	0	0	3	1
22	1	0	0	0	1	0	0	1	4	0	0	0	0	2	3	0	3	1
23	0	1	0	0	0	0	0	0	3	0	0	0	0	0	1	0	0	0
24	1	0	0	0	0	0	0	0	2	0	0	0	0	0	3	0	0	0
25	1	0	0	0	0	0	0	0	2	2	3	0	0	0	0	0	0	0

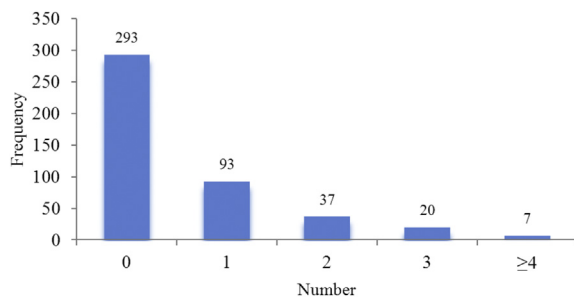


Fig. 9. The distribution of the numbers of co-rated restaurants.

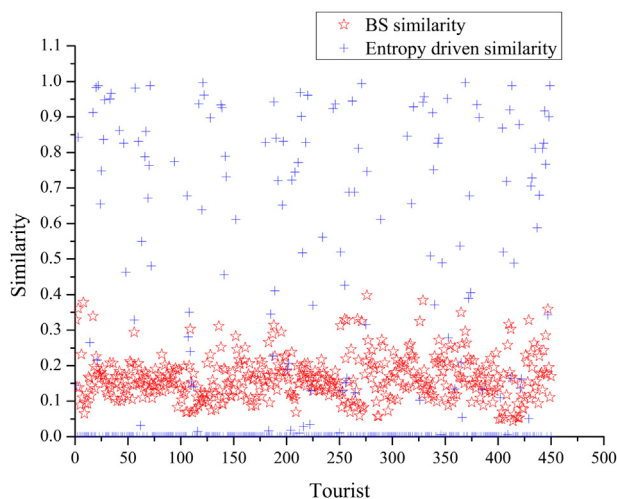


Fig. 10. Comparison of the degrees of the BS and entropy-driven similarity between TrevorHall and each of the 450 tourists.

measurements like the cosine similarity model (Salton & McGill, 1986).

Fig. 10 depicts the distributions of the degrees of the BS and entropy-based similarity measurements between TrevorHall and each of the other 450 tourists. As Fig. 10 shows, great differences exist between the distributions of these two types of similarities. The similarity degrees obtained by the BS measurement primarily range from 0.05 to 0.4, while those obtained by the entropy-based similarity measurement range from 0 to 1. Most entropy-based similarities are zero, but most of the BS similarities lie within [0.1, 0.25], as seen in the intensity degree of points in Fig. 10. The reason behind these differences lies in the sparsity of the dataset.

Table 4 presents the similarities obtained by our proposed similarity measurement, which linearly combines the BS and entropy-driven similarities, and the precision of the values in Table 4 is specified as one decimal place. To offer clear visual representation, Fig. 11 describes the distribution of the similarities obtained by our proposed similarity measurement.

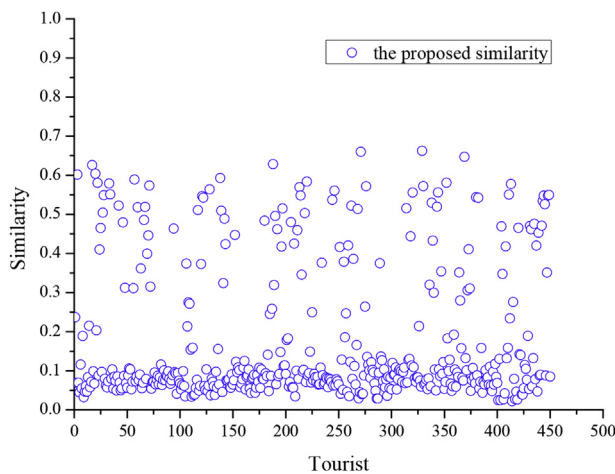
The similarities illustrated in Fig. 11 differ greatly from those in Fig. 10. In Fig. 11, the similarities range from 0.01 to 0.7, and their values are mainly confined to the interval [0.02, 0.1]. Furthermore, there is scarcely any similarity degree with a zero value. In other words, the proposed similarity measurement can effectively deal with sparse data. In addition, as shown in Table 4 and Fig. 11, some values in Table 4 equal zero while all similarities in Fig. 11 are greater than zero. The reason for this discrepancy between Table 4 and Fig. 11 is explained as follows. The values in Table 4 are determined by rounding the proposed similarities which are presented in Fig. 11 to one decimal place. That is to say, the similarity whose value is zero in Table 4 actually is greater than zero and less than 0.5.

Table 5 lists weight estimation results for the four criteria across the three integration functions, namely the WA, WBM, and WGBM integration functions. The weight vector varies with integration function. Service is the most important criterion when utilizing the WA and WGBM integration functions, while food is the most important criterion for the WBM integration function.

Table 4

The similarities obtained by the proposed similarity measurement.

Consumer (th)	Restaurant(th)																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	0.2	0.1	0.1	0.1	0.1	0	0.1	0.1	0.2	0.1	0.4	0.6	0.1	0.2	0.1	0.1	0	0.1
2	0.1	0.5	0.1	0.1	0.1	0.1	0.4	0.1	0.2	0.1	0	0.1	0.1	0.1	0.6	0.1	0.1	0.1
3	0.6	0.5	0.1	0.1	0.1	0.6	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0	0.1
4	0.1	0.1	0.1	0.1	0.1	0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.7	0.1	0.1	0.5	0.2
5	0	0.1	0.1	0.1	0	0.1	0.1	0.5	0.5	0.1	0.4	0.1	0.1	0.6	0.1	0.5	0.3	0.1
6	0.1	0.1	0.3	0.1	0.4	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0	0.5
7	0.1	0.1	0.6	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0	0.5	0	0.5
8	0.2	0.6	0.1	0.1	0.3	0	0.1	0.1	0.4	0.1	0	0.1	0.1	0.1	0.1	0.1	0.4	0.1
9	0	0.6	0.1	0.1	0.3	0.1	0.1	0	0	0.4	0.4	0.1	0.1	0.1	0.2	0.1	0.1	0.1
10	0	0.1	0.5	0.1	0.2	0.1	0.1	0.2	0.1	0.1	0	0	0.1	0.1	0.1	0.2	0.2	0.5
11	0.1	0.1	0.1	0.1	0	0.2	0.1	0.1	0.5	0.1	0.1	0	0.1	0.3	0.1	0	0.6	0.1
12	0	0.1	0.1	0.1	0.2	0.1	0.1	0.3	0.1	0.1	0.5	0	0.1	0.1	0.1	0.1	0.2	0.4
13	0.1	0.1	0.4	0.1	0	0.6	0.1	0.6	0.6	0.1	0.1	0.1	0.1	0.5	0.1	0.1	0.6	0
14	0.2	0.1	0.1	0.1	0	0.5	0.1	0.3	0.5	0.1	0.4	0.4	0.5	0.4	0.4	0.1	0	0.5
15	0.1	0	0.1	0.1	0.1	0	0.1	0.5	0.3	0.1	0.1	0.1	0.1	0.3	0.3	0.1	0.3	0.1
16	0.1	0.1	0.5	0.1	0.1	0.3	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.1
17	0.6	0.5	0.5	0.1	0.5	0.5	0	0.5	0.1	0.1	0.2	0.1	0.1	0	0.1	0.1	0	0.5
18	0.1	0.1	0.1	0.1	0	0.4	0.1	0.1	0.5	0.1	0.5	0.1	0.4	0.5	0.1	0.1	0	0.5
19	0.1	0.1	0.4	0.5	0.1	0.1	0.1	0.1	0.1	0.5	0	0.1	0.1	0.6	0.6	0.1	0	0.5
20	0.6	0.1	0.4	0.1	0.4	0.1	0.1	0.1	0.6	0.1	0	0.1	0.6	0.1	0.1	0	0.5	0.5
21	0.2	0.5	0.6	0.1	0.5	0.1	0	0.4	0.1	0.6	0.7	0	0.1	0.1	0.1	0.1	0.1	0.1
22	0.6	0.1	0.3	0	0.5	0.1	0.1	0.5	0.1	0.1	0	0.1	0.1	0.4	0.3	0.1	0.1	0.4
23	0.1	0.3	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0	0.1	0.1	0.1	0.4	0.1	0	0.5
24	0.4	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.3	0.1	0	0.5
25	0.5	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.3	0.1	0.1	0.1	0	0.1	0.1	0.1

**Fig. 11.** The distribution of the similarities obtained by the proposed similarity measurement.**Table 5**

The weights of the four criteria.

Integration function	Criteria			
	Food	Service	Value	Atmosphere
WA	0.04	0.80	0.12	0.04
WBM	0.95	0.03	0.01	0.01
WGBM	0.05	0.85	0.05	0.05

Table 6 lists the predictions for the 18 restaurants according to the proposed decision support model, and Table 7 provides the same predictions according to the four benchmark decision support models discussed in Subsection 3.2.

It is difficult to assess the performance of the six models based solely on the data in Tables 6 and 7. To illustrate the performance of each model, Table 8 introduces the actual online reviews by the target tourist TrevorHall, as they compare with predictions obtained by each of the six models. The numerical values are rated directly by TrevorHall, and IVNNs are produced from TrevorHall's text reviews. Table 9 provides the MAE_IVNN values, the metric presented in Subsection 3.3, for the six models to reflect the performance of the models.

As illustrated in Table 9, the MAE_IVNN of the entropy model is the largest. The MAE_IVNN values of both the IVNWB and IVNWGB models are smaller than that of the IVNNWA model. Moreover, the performance of the IVNWB model is better compared to that of the IVNWBES model.

4.2. Discussion

This case study reveals that the proposed decision support model can be effectively and practically applied in TripAdvisor.com to help independent tourists find satisfactory restaurants. In this subsection, we explore the reasons for the differences presented in Table 9 in order to discover the merits and drawbacks of each model.

The reasons for the differences among the six models' performance can be explained as follows. The Entropy model performs worst among the six models because the single-criterion ratings utilized in the Entropy model express less information than multi-criteria ratings which the other models use. Furthermore, entropy-

Table 6

Predictions of restaurants using IVNNWB and IVNWGB models.

Restaurant (th)	Model	
	IVNNWB	IVNWGB
1	$\langle [0.77, 1], [0, 0.18], [0, 0.23] \rangle$	$\langle [0.86, 1], [0, 0.13], [0, 0.13] \rangle$
2	$\langle [0.61, 1], [0, 0.26], [0, 0.38] \rangle$	$\langle [0.71, 1], [0, 0.15], [0, 0.26] \rangle$
3	$\langle [0.61, 1], [0, 0.26], [0, 0.38] \rangle$	$\langle [0.75, 1], [0, 0.15], [0, 0.23] \rangle$
4	$\langle [0.50, 1], [0, 0.31], [0, 0.50] \rangle$	$\langle [0.52, 1], [0, 0.25], [0, 0.45] \rangle$
5	$\langle [0.80, 1], [0, 0.17], [0, 0.20] \rangle$	$\langle [0.86, 1], [0, 0.11], [0, 0.13] \rangle$
6	$\langle [0.86, 1], [0, 0.14], [0, 0.15] \rangle$	$\langle [0.87, 1], [0, 0.11], [0, 0.12] \rangle$
7	$\langle [0.80, 1], [0, 0.17], [0, 0.20] \rangle$	$\langle [0.79, 1], [0, 0.13], [0, 0.19] \rangle$
8	$\langle [0.84, 1], [0, 0.15], [0, 0.16] \rangle$	$\langle [0.88, 1], [0, 0.11], [0, 0.11] \rangle$
9	$\langle [0.79, 0.99], [0, 0.18], [0, 0.21] \rangle$	$\langle [0.83, 1], [0, 0.12], [0, 0.17] \rangle$
10	$\langle [0.77, 0.98], [0, 0.18], [0, 0.23] \rangle$	$\langle [0.80, 1], [0, 0.14], [0, 0.19] \rangle$
11	$\langle [0.80, 0.99], [0, 0.17], [0, 0.20] \rangle$	$\langle [0.85, 1], [0, 0.11], [0, 0.14] \rangle$
12	$\langle [0.83, 1], [0, 0.15], [0, 0.17] \rangle$	$\langle [0.89, 1], [0, 0.15], [0, 0.10] \rangle$
13	$\langle [0.79, 1], [0, 0.17], [0, 0.21] \rangle$	$\langle [0.83, 1], [0, 0.11], [0, 0.15] \rangle$
14	$\langle [0.84, 1], [0, 0.15], [0, 0.16] \rangle$	$\langle [0.87, 1], [0, 0.11], [0, 0.12] \rangle$
15	$\langle [0.77, 1], [0, 0.18], [0, 0.22] \rangle$	$\langle [0.82, 1], [0, 0.15], [0, 0.17] \rangle$
16	$\langle [0.69, 1], [0, 0.23], [0, 0.31] \rangle$	$\langle [0.76, 1], [0, 0.15], [0, 0.22] \rangle$
17	$\langle [0.71, 1], [0, 0.21], [0, 0.29] \rangle$	$\langle [0.73, 1], [0, 0.16], [0, 0.26] \rangle$
18	$\langle [0.83, 1], [0, 0.15], [0, 0.17] \rangle$	$\langle [0.81, 1], [0, 0.12], [0, 0.18] \rangle$

Table 7

Predictions of restaurants using Entropy, CFWA, IVNNWA and IVNWBES models.

Restaurant (th)	Model			
	Entropy	CFWA	IVNNWA	IVNWBES
1	3.62	4.21	$\langle [0.81, 1], [0, 0.16], [0, 0.17] \rangle$	$\langle [0.73, 1], [0, 0.20], [0, 0.27] \rangle$
2	3.86	3.37	$\langle [0.64, 1], [0, 0.19], [0, 0.32] \rangle$	$\langle [0.56, 1], [0, 0.28], [0, 0.43] \rangle$
3	2.96	3.33	$\langle [0.69, 1], [0, 0.19], [0, 0.29] \rangle$	$\langle [0.57, 1], [0, 0.28], [0, 0.43] \rangle$
4	0.63	2.23	$\langle [0.43, 1], [0, 0.30], [0, 0.54] \rangle$	$\langle [0, 0], [0.34, 0.43], [1, 1] \rangle$
5	3.98	4.18	$\langle [0.82, 1], [0, 0.14], [0, 0.17] \rangle$	$\langle [0.81, 1], [0, 0.17], [0, 0.19] \rangle$
6	4.55	4.49	$\langle [0.83, 1], [0, 0.14], [0, 0.16] \rangle$	$\langle [0.86, 1], [0, 0.14], [0, 0.14] \rangle$
7	5.06	3.90	$\langle [0.75, 1], [0, 0.16], [0, 0.23] \rangle$	$\langle [0.86, 0.99], [0, 0.14], [0.01, 0.14] \rangle$
8	4.68	4.53	$\langle [0.85, 1], [0, 0.14], [0, 0.14] \rangle$	$\langle [0.85, 1], [0, 0.14], [0, 0.15] \rangle$
9	3.58	3.89	$\langle [0.78, 1], [0, 0.16], [0, 0.21] \rangle$	$\langle [0.79, 1], [0, 0.17], [0, 0.21] \rangle$
10	3.77	3.70	$\langle [0.75, 1], [0, 0.17], [0, 0.23] \rangle$	$\langle [0.71, 1], [0, 0.20], [0, 0.29] \rangle$
11	4.09	4.20	$\langle [0.80, 1], [0, 0.14], [0, 0.18] \rangle$	$\langle [0.80, 1], [0, 0.17], [0, 0.20] \rangle$
12	4.43	4.54	$\langle [0.86, 1], [0, 0.17], [0, 0.13] \rangle$	$\langle [0.86, 1], [0, 0.14], [0, 0.14] \rangle$
13	4.45	4.19	$\langle [0.79, 1], [0, 0.14], [0, 0.19] \rangle$	$\langle [0.73, 1], [0, 0.19], [0, 0.26] \rangle$
14	4.57	4.48	$\langle [0.84, 1], [0, 0.14], [0, 0.15] \rangle$	$\langle [0.84, 1], [0, 0.15], [0, 0.16] \rangle$
15	3.69	4.01	$\langle [0.77, 1], [0, 0.18], [0, 0.21] \rangle$	$\langle [0.73, 1], [0, 0.20], [0, 0.27] \rangle$
16	3.80	3.42	$\langle [0.70, 1], [0, 0.19], [0, 0.28] \rangle$	$\langle [0.76, 1], [0, 0.19], [0, 0.24] \rangle$
17	3.38	3.48	$\langle [0.67, 1], [0, 0.20], [0, 0.31] \rangle$	$\langle [0.71, 1], [0, 0.21], [0, 0.28] \rangle$
18	3.98	3.98	$\langle [0.76, 1], [0, 0.16], [0, 0.22] \rangle$	$\langle [0.81, 1], [0, 0.16], [0, 0.18] \rangle$

Table 8

The real online reviews in the form of numerical values and IVNNs.

Restaurant (th)	Data form	
	Real numbers	IVNNs
1	4.25	$\langle [0.8, 0.9], [0.025, 0.125], [0.1, 0.2] \rangle$
2	1	$\langle [0.15, 0.25], [0.35, 0.45], [0.75, 0.85] \rangle$
3	2	$\langle [0.35, 0.45], [0.35, 0.45], [0.55, 0.65] \rangle$
4	3	$\langle [0.55, 0.65], [0.15, 0.25], [0.35, 0.45] \rangle$
5	4.67	$\langle [0.88, 0.98], [0, 0.08], [0.017, 0.117] \rangle$
6	5	$\langle [0.9, 1], [0, 0.1], [0, 0.1] \rangle$
7	5	$\langle [0.9, 1], [0, 0.1], [0, 0.1] \rangle$
8	4	$\langle [0.75, 0.85], [0.05, 0.15], [0.15, 0.25] \rangle$
9	4	$\langle [0.75, 0.85], [0.05, 0.15], [0.15, 0.25] \rangle$
10	4	$\langle [0.75, 0.85], [0.05, 0.15], [0.15, 0.25] \rangle$
11	4.5	$\langle [0.85, 0.95], [0, 0.1], [0.05, 0.15] \rangle$
12	4.5	$\langle [0.85, 0.95], [0, 0.1], [0.05, 0.15] \rangle$
13	3	$\langle [0.55, 0.65], [0.15, 0.25], [0.35, 0.45] \rangle$
14	4	$\langle [0.8, 1], [0, 0.1], [0, 0.1] \rangle$
15	4.4	$\langle [0.83, 0.93], [0.01, 0.11], [0.07, 0.17] \rangle$
16	4	$\langle [0.6, 0.85], [0.05, 0.15], [0.15, 0.25] \rangle$
17	4	$\langle [0.75, 0.85], [0.05, 0.15], [0.15, 0.25] \rangle$
18	4.75	$\langle [0.9, 1], [0, 0.075], [0, 0.1] \rangle$

based similarity measurement is unsuitable for sparse data. The IVNNWA model, which utilizes IVNN ratings, performs much better than the CFWA model, which utilizes ratings in the form of real data; this is because IVNNs can use more information from ratings compared to real data. Both the IVNNWB and IVNWGB models outperform the IVNNWA model, indicating the validity of applying the IVNNWBM and IVNWGBM. Both of these two operators take into account the interdependence among criteria, while the WA operator for IVNNs used in the IVNNWA model does not. Last but not least, the IVNNWB model is more accurate than the IVNWBES model. The IVNWBES model employs the entropy-driven similarity measurement to obtain tourist similarities, while the IVNNWB model uses the proposed similarity

Table 9

The values of MAE_IVNN of the six different models (the proposed in bold).

Model	Entropy	CFWA	IVNNWA	IVNWBES	IVNNWB	IVNWGB
MAE_IVNN	0.7781	0.6587	0.1178	0.1269	0.1130	0.1162

measurement. However, as shown in Figs. 5 and 6, the data in our empirical study are sparse, which leads to the exactitude loss of the similarities attained by the entropy-driven similarity measurement. This suggests that it is better to take advantage of the proposed similarity measurement rather than the entropy-driven similarity measurement in this context.

Consequently, the case study shows that the proposed model can provide decision support with more faith to potential tourists' preferences than other models in TripAdvisor.com. Thus, the proposed model is practicable and effective.

One may argue that the new decision support model faces the problem of large time consumption due to online reviews' large amount like other decision support models utilizing online reviews. In practical application, the problem of large time consumption can be eased by combining online, nearline and offline modes. Please refer to (Amatriain, 2013) for more details about online, nearline and offline modes. Moreover, the online reviews have timeliness. For the dataset, it is not necessary to include all reviews, but reviews posted within a period of time from now, like within six months. Another problem one may argue is the difficulty of live updating offline dataset because of the exponential growth of online reviews. Nevertheless, the influence of this limitation is small because the requirement for timeliness is not that severe when recommending restaurants on tourism websites. In practical application, the offline dataset can be updated at scheduled short time intervals like one month.

5. Conclusion and future research

This study establishes a comprehensive decision support model that utilizes social information to assist independent tourists on TripAdvisor.com in finding satisfactory restaurants. In contrast to traditional decision support models, the proposed model makes full use of social information including online reviews and social relationships, and it takes into consideration interdependence among criteria by employing the IVNWB or IVNWGBM integration functions. In addition, this study develops a novel similarity measurement for obtaining similarities accurately with the sparse data; this measurement, which combines the entropy-based similarity and novel BS measurements, is developed and used in the proposed model. The proposed decision support model is validated via a case study using data from TripAdvisor.com. The results reveal that the proposed decision support model can be effectively applied to the practical social tourism website TripAdvisor.com.

This study contributes to proposing a decision support model to provide better services for tourists on TripAdvisor.com than extant models. From the perspective of practical application, the utilization of IVNNs in the proposed decision support model reduces the loss of information compared with real numbers. The decision support model introduces IVNNs to describe active, neutral and passive information as well as uncertainty in tourists' reviews all at once. The performance of the model with IVNNs is proven by the case study with data from TripAdvisor.com to be better than that of the model with real numbers. Moreover, the idea of the proposed decision support model can be applied to TripAdvisor.com as well as other third-party tourism websites and applications under the guidance of its algorithm given in Appendix B to improve the extant decision support system. Our case study on TripAdvisor.com illustrates that the proposed decision support model is able to provide better decision support service for tourists than the extant decision support models. At the same time, as to the tourism website, the application of the proposed decision support model will enhance its tourist satisfaction and loyalty; as for the restaurant on TripAdvisor.com, its sales will

boost with increasing performance of decision support model. From the perspective of theory, the new tourist similarity measurement, which overcomes the defect of extant similarity measurements, is able to deal with sparse data under fuzzy environments. And our case study verifies that the model using the new similarity measurement is superior to the model using extant similarity measurement in accuracy. In addition, the consideration of the interdependence among criteria conforms to tourists' practical decision-making. The proposed decision support model considers the interdependence among criteria by employing the IVNWB and IVNWGBM integration functions to integrate multi-criteria predictions. The results of our case study indicate that the model with the proposed integration functions performs better than those based on the assumption of independent criteria.

This study makes the above contributions but also results in some limitations that guide us towards several promising directions for future research. First, the computation of the model is somewhat complex. As pointed by extant researches and surveys, the user satisfaction toward a website falls with increasing waiting time (Kumar, Batista, & Maull, 2011). It would be fruitful to simplify the complexity of the calculation without affecting the accuracy of the decision support model. Second, the study puts forward the idea of introducing IVNNs to denote online reviews without studying the technology of transforming online reviews into IVNNs. In order to apply the research results to practice, it is necessary to build proper emotion directory and determine the active, neutral and passive degrees. Third, besides numerical ratings and text reviews, meal pictures posted by tourists may influence potential tourists' decision-making. We will study how to take into account the influence of meal pictures to improve the decision support model. The study will mainly consist of two parts. The first part will focus on the possible different influences of meal pictures on active and passive reviews. And the second one will be about how to quantify the influence of meal picture. Fourth, we will try to consider the different influences of active ($[A^-, A^+]$), neutral ($[N^-, N^+]$) and passive ($[P^-, P^+]$) information in the future research. Researchers suggested that tourists may pay more attention to passive information than active and neutral information about restaurants since they deemed that the first type of information is more credible than the latter two types (Fang et al., 2016). Yet passive information gets no special treatment in the proposed decision support model.

Conflict of interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Appendix A. Formulae of the IVNWB and IVNWGBM operators

Let $pred_i^j = \langle [A_i^-, A_i^+], [N_i^-, N_i^+], [P_i^-, P_i^+] \rangle$ ($j = 1, 2, \dots, n$) be a collection of predictions under each criterion c_j about restaurant i , while $W = (w_1, w_2, \dots, w_n)^T$ is the weight vector of c_j ($j = 1, 2, \dots, n$) where $w_j > 0$ ($j = 1, 2, \dots, n$) and $\sum_{j=1}^n w_j = 1$. Then, the overall prediction value r_i of restaurant i can be obtained by the IVNWB operator as follows:

$$\begin{aligned}
r_i = IVNWBM^{t,q}(pred_i^1, pred_i^2, \dots, pred_i^n) = & \left(\left[\left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (A_i^{c-})^{w_c} \right)^t \left(1 - (A_i^{j-})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}}, \right. \right. \\
& \left. \left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (A_i^{c+})^{w_c} \right)^t \left(1 - (A_i^{j+})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}} \right], \\
& \left[1 - \left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (N_i^{c-})^{w_c} \right)^t \left(1 - (N_i^{j-})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}}, \right. \\
& \left. 1 - \left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (N_i^{c+})^{w_c} \right)^t \left(1 - (N_i^{j+})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}} \right], \\
& \left[1 - \left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (P_i^{c-})^{w_c} \right)^t \left(1 - (P_i^{j-})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}}, \right. \\
& \left. 1 - \left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (P_i^{c+})^{w_c} \right)^t \left(1 - (P_i^{j+})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}} \right] \Bigg)^{\frac{1}{t+q}},
\end{aligned} \tag{A1}$$

or the overall prediction value r_i of restaurant i can be obtained by the IVNWGBM operator as follows:

The values of parameters t and q influence the accuracy of the decision support model and rest with the subjective preferences of tourist u . For more information about the influence of t and q , please refer to (Tian et al., 2015; Zhu & Xu, 2013).

$$\begin{aligned}
r_i = IVNWGBM^{t,q}(pred_i^1, pred_i^2, \dots, pred_i^n) = & \left(\left[1 - \left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (A_i^{c-})^{w_c} \right)^t \left(1 - (A_i^{j-})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}}, \right. \right. \\
& \left. 1 - \left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (A_i^{c+})^{w_c} \right)^t \left(1 - (A_i^{j+})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}} \right], \\
& \left[\left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (1 - N_i^{c-})^{w_c} \right)^t \left(1 - (1 - N_i^{j-})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}}, \right. \\
& \left. \left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (1 - N_i^{c+})^{w_c} \right)^t \left(1 - (1 - N_i^{j+})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}} \right], \\
& \left[\left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (1 - P_i^{c-})^{w_c} \right)^t \left(1 - (1 - P_i^{j-})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}}, \right. \\
& \left. \left(1 - \prod_{\substack{c,j=1 \\ c \neq j}}^n \left(1 - \left(1 - (1 - P_i^{c+})^{w_c} \right)^t \left(1 - (1 - P_i^{j+})^{w_j} \right)^q \right)^{\frac{1}{n(n-1)}} \right)^{\frac{1}{t+q}} \right] \Bigg)^{\frac{1}{t+q}}.
\end{aligned} \tag{A2}$$

Appendix B. The algorithm of the proposed decision support model

We present the algorithm of the proposed decision support model based on the illustration in Section 2 as follows.

Algorithm. The decision support model for TripAdvisor.com with social information.

Input: tourist-restaurant rating matrix TRR , restaurant rating distribution matrix RD

Output: the predictive rating of u about restaurant i

Steps:

1. for each rating rr_{ig} in TRR
 2. transform rr_{ig} into IVNN (denoted by r_{ig}) according to Table 1;
 3. end
 4. obtain the average rating au of u
 5. initialize the variable $sum_sim=0$;
 6. for each v_i who rated i
 7. obtain the average rating of v_i denoted by av_i
 8. for each restaurant j rated by both u and v_i
 9. obtain the difference d_{vij} between the rating of j rated by v_i and av_i ;
 10. obtain the difference d_{uj} between the rating of j rated by u and au ;
 11. obtain the absolute value ad_j of the difference between d_{vij} and d_{uj} ;
 12. add ad_{vij} to matrix AD ;
 13. end
 14. obtain the sum sum_{vij} of ad_{vij} ;
 15. obtain the entropy-driven similarity $sim_Entropy(u, v_i)$ between u and v_i by Eq. (1);
 16. initialize the variable $sim_BS(u, v_i)=0$;
 17. for each restaurant i rated by v_i
 18. obtain the rating distribution of i from RD ;
 19. for each restaurant q rated by u
 20. obtain the rating distribution of q from RD ;
 21. obtain the similarity $bc(i, q)$ between i and q by Eq. (6);
 22. obtain the local similarity $loc(r_{v_i i}, r_{u q})$ by Eq. (5);
 23. obtain $sim_BS(u, v_i)=sim_BS(u, v_i)+loc(r_{v_i i}, r_{u q}) * bc(i, q)$;
 24. end
 25. end
 26. obtain the proposed similarity $sim(u, v_i)$ by Eq. (7);
 27. obtain $sum_sim=sum_sim+sim(u, v_i)$;
 28. end
 29. initialize the variable $non_pred_{ig}=0$;
 30. for each v_i who rated i
-

-
31. for each criterion c_g
 32. obtain the non-normalized predictive rating of u about j under criterion c_g by

$$non_pred_{jg} = non_pred_{jg} + sim(u, v_i) * r_{vijg};$$

$$r_{vijg}$$
 represents the rating of j rated by v_i under criterion c_g
 33. end
 34. obtain the normalized predictive rating of u about j under criterion c_g by

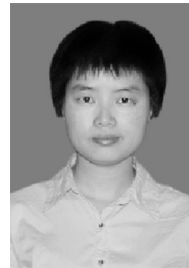
$$pred_{jg} = non_pred_{jg} / sum_sim;$$
 35. end
 36. initialize the variable $pred_j$;
 37. for each criterion c_g
 38. obtain the comprehensive predictive rating of u about j by $pred_j = pred_j + w_g * pred_{jg}$; w_g represents the weight of criterion c_g obtained by the regression analysis with ratings provided by u
 39. end
 40. return $pred_j$;
-

The algorithm mainly comprises four parts. The first part, which includes the first three lines, transforms ratings in the form of real data into IVNNs. Lines 4–28 depict the second part. Three kinds of similarity are obtained in the second part: the entropy-driven similarity is obtained by lines 4–15; the BS degree is obtained through codes from line 16 to line 25; the proposed similarity is obtained in line 26. The third part, which ranges from line 26 to line 35, aims at determining the predictive rating of tourist u about restaurant j under each criterion. Moreover, the comprehensive predictive rating of tourist u about restaurant j is obtained by the codes in the rest lines.

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