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A Multi-Criteria Decision Support Model for Restaurant Selection Based on Users' Demand Level: The Case of Dianping.com

Ziwei Shu [a,*], Ramón Alberto Carrasco [b], Manuel Sánchez-Montañés [c], Javier Portela García-Miguel [a]

[a] Department of Statistics and Data Science, Faculty of Statistics, Complutense University of Madrid, 28040 Madrid, Spain
[b] Department of Marketing, Faculty of Statistics, Complutense University of Madrid, 28040 Madrid, Spain
[c] Department of Computer Science, Escuela Politécnica Superior, Universidad Autónoma de Madrid, 28049 Madrid, Spain

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ABSTRACT

The Internet, by offering a variety of information sources such as online reviews, aids people in selecting restaurants. However, it also prolongs their decision-making process due to the need to integrate information across multiple criteria. Existing decision support models for choosing satisfactory restaurants overlook users' varying demand levels for each aspect of the restaurant, making the process less efficient. This paper aims to develop a multi-criteria decision support model for users to efficiently and accurately rank and select restaurants based on their demand level for various restaurant aspects. The 2-tuple linguistic ordered weighted averaging (2LOWA) aggregation operator is applied for the first time to aggregate user ratings, generating linguistic ratings that mirror the diverse levels of user demand for restaurant service, food, and environment. The importance weights (IW) method is introduced to calculate linguistic weights, thereby obtaining customized 2T-SFE composite scores under various user demand scenarios. The proposed model's applicability is demonstrated using a dataset comprising over 3.7 million reviews sourced from Dianping.com. The results show multiple personalized restaurant rankings with more linguistically understandable composite scores, enabling users to efficiently choose a suitable restaurant based on their preferences and requirements. Moreover, a list of restaurants satisfying most users with different demand levels can be generated by assessing their frequency of appearance in the top 10 restaurants across over 340 scenarios established by the proposed model. This contributes to offering more reliable and comprehensive restaurant recommendations and rankings, ultimately increasing customer satisfaction in the selection process.

1. Introduction

The development of the Internet has empowered individuals to access a wealth of information before making decisions. The swift evolution of social media has significantly changed the way information is acquired and disseminated, with electronic word of mouth (eWOM) playing a crucial role. Henning-Thurau et al. (2004) defined eWOM as "any positive or negative statement made by potential, actual, or former customers about a product or company that is made available to a multitude of people and institutions via the

* Corresponding author.
E-mail addresses: ziweishu@ucm.es (Z. Shu), ramoncar@ucm.es (R.A. Carrasco), manuel.smontanes@uam.es (M. Sánchez-Montañés), jportela@estad.ucm.es (J.P. García-Miguel).

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Internet." The eWOM plays a crucial role in furnishing necessary information to potential customers (Jeong & Jang, 2011). The eWOM assists customers in evaluating options and eliminates ambiguity in the decision-making process, thereby reducing both cost and time (Lee, 2014). Online reviews, typically composed of a star rating and a textual comment, serve as representative forms of eWOM and are widely recognized as reliable sources of information (Yang et al., 2015). Review sites such as TripAdvisor, Yelp, and Google Reviews are commonly used by both tourists and locals to discover suitable restaurants, hotels, or entertainment venues. These platforms provide opinions from previous customers, facilitating decision-making and minimizing the risk of a negative experience.

When selecting a restaurant, most customers typically read online reviews of the restaurant before making their choice (Carter, 2022). Online reviews serve as reference points for many people when deciding which restaurant to choose (Tuş & Adalı, 2022). According to TripAdvisor's review research, 70% of restaurant customers consider online reviews crucial in their decision-making process (DiegoCoquillat.com, 2022). For instance, favorable reviews (i.e., positive eWOM) increase the restaurant's clientele by informing customers that the restaurant's cuisine is delicious, and the environment is excellent. Online reviews are crucial for customers without knowledge about restaurants when selecting a suitable restaurant (Shambour et al., 2023). They show evaluations of several criteria of the restaurants, which influence customers' choices (Rahman et al., 2022). Food, service quality, and environment are the three most commonly agreed-upon criteria that affect restaurant survival and ranking (Parsa et al., 2005; Ryu & Jang, 2007; DiPietro et al., 2011; Jeong & Jang, 2011; Ryu et al., 2012; Jurafsky et al., 2014). Bertan's research indicates that five criteria influence restaurant rankings: food and beverage, ingredients, personnel, environment, and service (Bertan, 2020). Hartanto and Utama (2020) used seven parameters to create restaurant recommendations: customer interest, budget, distance between the customer and the restaurant, taste rating, cleanliness rating, facilities rating, and halal or non-halal status.

Selecting the "optimal" restaurant from a collection of alternatives based on online reviews given by customers regarding various criteria (e.g., food, service, environment) is a Multi-Criteria Decision-Making (MCDM) problem (Ayşegül & Esra Aytaç, 2022). MCDM methods are characterized by taking into account multiple criteria, which are typically at odds with one another, as well as the preferences of the involved decision-makers (Roy, 1996). These methods fall within a category of approaches used in decision support models (Vatankhah et al., 2023). MCDM methods usually aggregate the scores of multiple factors (e.g., food, service quality,

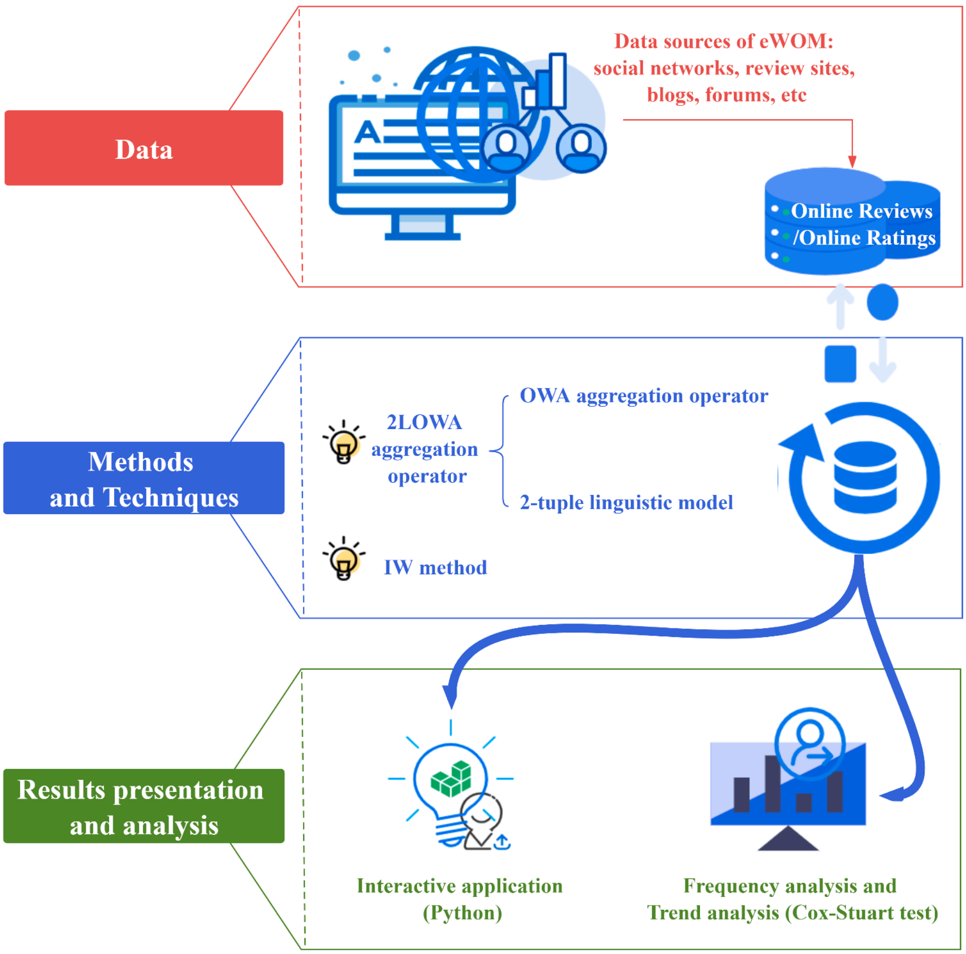

Fig. 1. Architecture for achieving the stated objective.

environment, price, etc.) into overall scores of diverse restaurants to facilitate their ranking. For instance, Osvaldo and Pangemanan (2016) applied the analytic hierarchy process (AHP) method to assist the customer in selecting restaurants. Zhang et al. (2017) developed a decision-support approach to help travelers use social information on TripAdvisor.com to select restaurants. In the literature, many MCDM techniques have been used for restaurant selection and ranking (Yildiz & Yildiz, 2015; Osvaldo & Pangemanan, 2016; Fang & Partovi, 2021; Bu & Zhang, 2021; Ayşegül & Esra Aytaç, 2022; Dyondra et al., 2023).

However, although existing models have contributed to the ranking and selection of restaurants based on online reviews, previous studies have overlooked the fact that users have diverse preferences for reading reviews due to their varying demands on different aspects of a restaurant. For example, a user who is more demanding of the restaurant's environment but tolerant of the service would read and focus more on negative reviews related to the restaurant's environment than those critiquing its service. In this scenario, relying solely on the average to calculate the overall restaurant score would not fully meet the user's needs.

Moreover, while certain review sites allow users to rank restaurants based on their preferences for specific criteria, such as environmental online ratings or food quality, they do not provide a direct way for users to obtain comprehensive restaurant rankings that align with their individualized preferences across various criteria at the same time. This makes it difficult to promptly recommend suitable restaurants to users, aiding them in decision-making when they have simultaneous demands for service, environment, or other aspects of the restaurant.

Therefore, the objective of this paper is to develop a multi-criteria decision support model to help users efficiently and accurately rank and select the restaurants based on their level of demand for various restaurant aspects. To achieve this, various sub-objectives are also set (see Section 2.2). Fig. 1 illustrates the use of distinct methods and techniques in this paper to achieve the stated objective.

Selecting an appropriate eWOM data source is important for assessing the feasibility of the proposed model. This paper leverages Dianping.com to gather user reviews on restaurants, assessing the practical application of the proposed model in restaurant ranking and selection. In terms of the methods and techniques employed to analyze and process collected user reviews into useful eWOM outcomes for the decision-making process, the proposed model employs the following ones:

- **2-tuple Linguistic Ordered Weighted Averaging (2LOWA) aggregation operator:** It is an extension of the Ordered Weighted Averaging (OWA) aggregation operator, incorporating the 2-tuple linguistic model. The 2-tuple linguistic model is applied in the OWA aggregation operator for three reasons: (i) it allows aggregating information without loss; (ii) it makes the aggregation results easier to understand; (iii) it can perform transformations between 2-tuple values and numerical values, so that weight calculation and composite score computation will not be a problem. Various linguistic quantifiers from the 2LOWA aggregation operator, designed to represent different user demand levels, are applied to aggregate user ratings for each restaurant criterion. This process generates new criteria that reflect different levels of user demand concerning restaurant service, food, and environment.
- **Importance Weights (IW) method:** This method is introduced in this paper to calculate the linguistic weights of three restaurant criteria. It can generate importance weights related to the level of user demand for the different restaurant criteria, thereby enabling the calculation of the composite score for each restaurant using more accurate linguistic weights. This method allows review platforms to provide users with a list of top-ranked personalized restaurants, making it easier for users to select restaurants.

To sum up, the proposed model introduces a novel approach to restaurant ranking and selection, using the 2LOWA aggregation operator and the IW method. This offers practical utility by enabling users to quickly find a suitable restaurant, as restaurant rankings are determined based on individual needs rather than solely on average ratings. The results of this approach, as depicted in Fig. 1, are presented through an interactive application created using the Python programming language. Through this application, users can specify their level of demand for various restaurant criteria, generating a personalized restaurant ranking to facilitate a more efficient restaurant selection process. Frequency analysis and trend analysis are also employed to study how restaurant rankings evolve with varying user demand levels. These analyses enable review sites to recommend restaurants that can meet the demands of the majority of users with different levels of demand based on the frequency of the restaurant appearing in the top 10 in a variety of scenarios.

The remainder of this paper is structured as follows. Section 2 provides an overview of models developed in recent years for restaurant selection and ranking based on online reviews, and indicates the research objectives of this paper. Section 3 introduces several fundamental concepts on which the proposed model is based. Section 4 demonstrates the application of the proposed model on a dataset comprising over 3.7 million reviews from Dianping.com. Section 5 analyzes the ranking and selection of restaurants under multiple scenarios. Section 6 discusses the advantages and disadvantages of the proposed model. Section 7 presents the conclusions of this work and explores possible future research directions.

2. Literature review and research objectives

Section 2.1 provides a literature review on decision support models for restaurant selection and ranking based on online reviews, with a primary focus on MCDM methods. The review spans from 2018 to the present, conducting a comparative analysis of existing methods to identify any gaps in the literature. Section 2.2 outlines the research objectives of this paper.

2.1. Restaurant selection and ranking based on online review

Decision support models help people make correct and on-target decisions (Minartiningtyas & Prawira, 2019). MCDM methods belong to decision support models (Vatankhah et al., 2023). A systematic search is conducted on the Web of Science, Scopus, and Google Scholar databases to explore studies related to restaurant selection and ranking based on online reviews, covering the period from 2018 to the present. This search encompasses articles published in the last five years, including 2018, as the papers from 2023 do not cover the entire year.

The following terms were used in the literature search query: "decision support models", "restaurant selection", "restaurant ranking", "Multi-Criteria Decision-Making", "online reviews", "online ratings", as well as their respective synonyms and abbreviations (e.g., "MCDM" for "Multi-Criteria Decision-Making"). The literature review process conducted in this study to identify pertinent and valid papers for the research is shown in Fig. 2. Table 1 presents works related to restaurant selection and ranking based on online reviews, outlining the eWOM data sources, methods and techniques employed in each study.

As can be seen in Table 1, many researchers have used MCDM methods like AHP, CRITIC, ELECTRE, and WP to address restaurant selection and/or ranking issues based on online reviews. Furthermore, some researchers have incorporated text mining techniques, deep learning models, recommender systems, and sensitivity analysis to assist customers in choosing restaurants based on online reviews.

However, to the best of our knowledge, existing research on restaurant selection and ranking lacks consideration of users' demand levels in the decision-making process. Specifically, previous research has not yet explored the application of the OWA aggregation operator to restaurant selection and ranking based on online reviews. This operator can aggregate evaluations of multiple criteria, taking into account the decision-maker's attitude. Moreover, the most commonly used eWOM data source in previous studies is TripAdvisor. Only a few papers have explored eWOM data sources from China, such as Dianping.com, Meituan, Ele.me, etc., to conduct research on restaurant selection and ranking.

To fill these voids, this paper proposes a novel approach that combines the 2LOWA aggregation operator (an extension of the OWA aggregation operator) with a new method to calculate linguistic weights introduced here, the IW method. This approach can produce customized 2T-SFE composite scores, catering to different user demand scenarios. Each of these scores fluctuates based on the level of user demand, enabling the creation of more personalized restaurant rankings to help users quickly choose suitable restaurants. These results are presented through an interactive application developed in Python, allowing users to specify their demand levels for various restaurant criteria and generate a personalized ranking.

2.2. Research objectives

Section 2.1 points out a literature gap concerning the consideration of users' demand levels in restaurant selection and ranking based on online reviews. Existing models have neglected the varied demand levels of each user for different aspects of restaurants. Therefore, the main objective of this paper is to develop a multi-criteria decision support model to help users efficiently and accurately rank and select the restaurants based on their level of demand for various restaurant aspects.

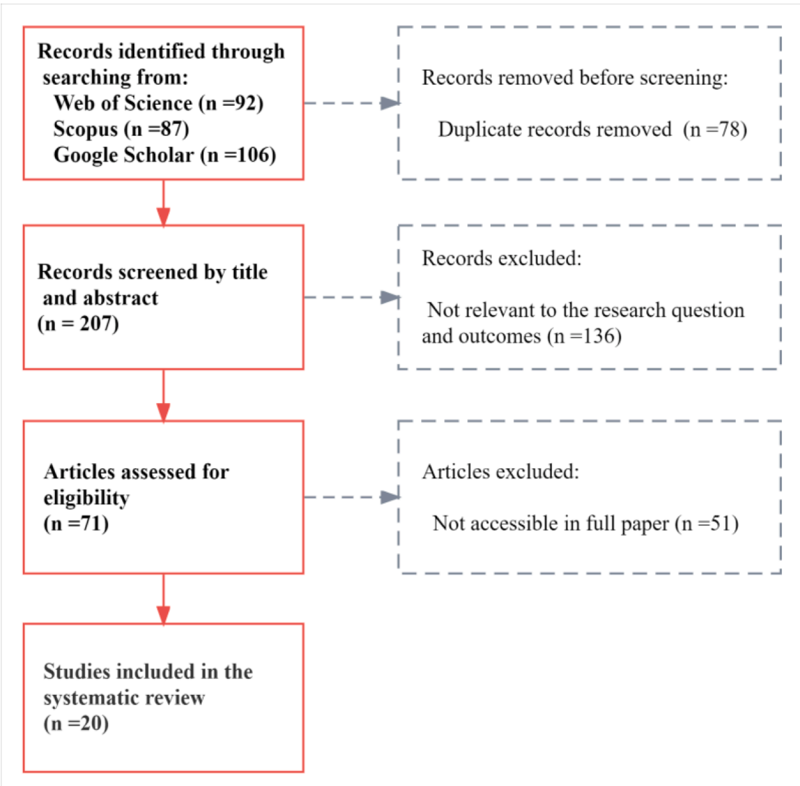

Fig. 2. Literature review flow diagram.

Table 1
Studies related to restaurant selection and ranking based on online reviews.

Author(s) (year)	eWOM data source(s)	Methods and techniques
Asadabadi et al. (2018)	Google Maps	Fuzzy Concept of Stratification (Fuzzy CST), Bi-Objective CST (BOCST)
Agüero-Torales et al. (2019)	TripAdvisor	Opinion mining, Valence Aware Dictionary for sEntiment Reasoning (VADER)
Minartiningtyas and Prawira (2019)	Google Maps	Weighted Product (WP), Geographic Information System (GIS)
Wardhani and Lutfina (2020)	Mobile Phone data	WP
Zhang et al. (2020b)	Yelp, Dianping.com	Deep Neural Network (DNN), Matrix Factorization (MF), Multi-View Visual Bayesian Personalized Ranking from implicit feedback method (MVBPR)
Asani et al. (2021)	TripAdvisor	Sentiment analysis, Agglomerative Hierarchical Clustering
Bu and Zhang (2021)	OpenRice	AHP
Fang and Partovi (2021)	TripAdvisor	AHP, Latent Dirichlet Allocation (LDA)
Liang et al. (2021)	Meituan, Ele.me	Content analysis, AHP, Probabilistic Linguistic Term Set (PLTS), Fuzzy Comprehensive Evaluation (FCE)
Jabreel et al. (2021)	TripAdvisor	ELECTRE-III, Support Vector Machine (SVM), Aspect-Based Sentiment Analysis (ABSA)
Zuheros et al. (2021)	TripAdvisor	Sentiment Analysis based Multi-person Multi-criteria Decision Making (SA-MpMcDM), ABSA, Convolutional Neural Networks (CNN), Long-Short-Term Memories (LSTM) networks, Multi-Task Learning (MTL)
Ayşegül and Esra Aytaç (2022)	TripAdvisor	Interval-Valued Intuitionistic Fuzzy-CRiteria Importance Through Intercriteria (IVIF-CRITIC), Combined Compromise Solution (CoCoSo)
Lee et al. (2022)	Yelp	User-Based Collaborative Filtering (UBCF) with filtering recommendation candidate
Angamuthu and Trojovský (2023)	TripAdvisor	Sentiment Analysis in Recommender Systems with Multi-person, Multi-criteria Decision Making (SAR-MCMD), Residual Attention CNN (RACNN), Bi-LSTM networks
Darko and Liang (2023)	TripAdvisor	Term Frequency-Inverse Document Frequency (TF-IDF), K-means, Probabilistic Linguistic Linear Programming Technique for Multidimensional Analysis of Preference (PL-LINMAP), Probabilistic Linguistic Measurement Alternatives and Ranking according to the COmpromise Solution (PL-MARCOS)
Dyondra et al. (2023)	TripAdvisor	AHP
Krishankumar et al. (2023)	TripAdvisor, Goibibo, Trivago	Probabilistic linguistic comprehensive (PLC), CRiteria Importance Through Intercriteria Correlation (CRITIC), Discriminative Weighted Muirhead Mean (DWMM) operator, Dempster–Shafer theory based Bayesian approximation (DSBA)
Novas et al. (2023a)	TripAdvisor	LDA, ELECTRE, Preference Ranking Organization Method for Enrichment Evaluation (Promethee)
Novas et al. (2023b)	TripAdvisor	Benchmark ranking model, Fuzzy logic, LDA
Tayal et al. (2023)	TripAdvisor	ABSA, Plithogenic sets-based MCDM

The following sub-objectives contribute to the achievement of the main objective:

1) To generate more personalized composite scores of restaurants.
2) To improve linguistic understanding of restaurant rankings.
3) To explore how restaurant rankings change based on user demand levels.
4) To offer users more reliable and comprehensive restaurant choices.
5) To examine the applicability of the proposed model by using a large database of online reviews.

3. Theoretical framework

This section introduces the fundamental concepts on which the proposed model is based. Section 3.1 presents the use of linguistic variables in online review platforms to express customer satisfaction regarding restaurants, with a specific focus on Dianping.com. Section 3.2 introduces the 2-tuple linguistic model that can solve the information loss problem of the fuzzy linguistic approach in linguistic term fusion. Section 3.3 introduces the OWA aggregation operator and its extension using the 2-tuple linguistic model (i.e., 2LOWA aggregation operator), as they can express the attitudinal character of the decision-maker in information aggregation. The linguistic quantifiers of the 2LOWA aggregation operator are used to aggregate users' evaluations of each restaurant criterion according to the user demand levels for various restaurant-related criteria. Section 3.4 presents the IW method that proposes in this paper to obtain the linguistic weight corresponding to the user demand level to compute the composite score for each restaurant.

3.1. Linguistic variables used on Dianping.com

Dianping.com, founded in April 2003, is one of the first Chinese life service review sites. It mainly provides recommendations to users on a variety of topics including restaurants, hotels, movie tickets, home improvement, beauty salons, sporting events, etc. It is widely regarded as a popular travel and dining platform in China. This platform makes it easy for users to exchange information, post reviews, and discover suitable hotels and restaurants. Users can access three different types of restaurant ratings on Dianping.com: ratings based on service, food, and environment. In addition, Dianping.com determines the restaurant's overall star rating based on these three criteria. It employs a five-star rating system that uses linguistic terms to express users' reviews of restaurants on these three criteria (dianping.com, 2022). Fig. 3 shows an example.

As shown in Fig. 3, user reviews on each restaurant criterion on Dianping.com can be considered as a linguistic variable. A linguistic variable is a variable whose values are words or sentences in a natural language (Zadeh, 1975). Linguistic terms are used in the fuzzy linguistic approach to reflect the approximate values of a linguistic variable since they are very similar to human thinking (Zadeh, 1975). Although the use of linguistic terms is less specific than the use of numerical values, it is much more in line with the way people express their thoughts. For example, in comparison to "The restaurant environment has a rating of 3," the statement "The restaurant environment is good" is less precise. The word "good" is a linguistic term for the variable "restaurant environment", which is less precise than the numerical value "3". However, the term "good" allows people to naturally express and deal with uncertain information (the user may not want to rate the restaurant environment with a 3, but with a 3.1, a 3.2, or a 2.9). In other words, the linguistic term "good" contains many more possible scores than just a 3. Therefore, using linguistic variables allows for achieving better modeling of the information concerned than using traditional numerical variables (Cid-López et al., 2015; Malik & Hussain, 2018; Hassan et al., 2022; Li et al., 2022).

In fact, except for Dianping.com, many restaurant review sites like TripAdvisor, OpenTable, Yelp, etc., employ the five-star rating system with linguistic terms to evaluate restaurants based on various criteria. This system ensures that users are not overwhelmed by too many or too few alternatives when rating, allowing them to express their opinions correctly. It is generally used with linguistic terms such as *Very Good, Good, Average, Poor, Very Poor*, etc. The arithmetic mean is typically used by review sites to aggregate ratings for various restaurant criteria to obtain an overall score, with restaurants ranked from highest to lowest.

Furthermore, the reviews on Dianping.com are reliable, as they are rigorously monitored by its algorithm. User reviews with missing partial dimensional ratings are considered spam reviews or intentionally bad reviews on Dianping.com (dianping.com, 2022). All reviews go through a rigorous filtering process before being published. For instance, a review written by a newly registered user will not be published, which prevents advertising or unfair competition among peers. Those users who have repeatedly written unreasonable or irresponsible reviews will be suspended. In addition, Dianping.com will not begin computing the restaurant's overall star rating until the restaurant receives ten or more reviews (Operation Research Institute, 2021).

Dianping.com applies its stringent guidelines to rank the restaurants, which gives it a unique competitiveness that its rivals cannot easily match. However, the method Dianping.com uses to aggregate user ratings of restaurants' various criteria could be improved. This paper advocates using the 2LOWA aggregation operator to aggregate user ratings rather than the arithmetic mean, so that new criteria that consider the different levels of user demand for restaurant service, food, and environment can be created. More information on the 2LOWA aggregation operator can be found in Section 3.3.

3.2. *The 2-tuple Linguistic model*

Many aspects of real life can be evaluated quantitatively, as well as qualitatively. As linguistic terms are very close to human thinking, several review sites, such as TripAdvisor, Trip.com Group, Dianping.com, etc., employ them to express user satisfaction with various aspects of hotels, restaurants, or attractions.

However, the fuzzy linguistic approach has a problem of information loss due to its information representation model and the computation methods used in the linguistic term fusion processing (Herrera & Martínez, 2000). To address this problem, Herrera and Martínez developed the 2-tuple linguistic model, which expresses information by means of linguistic values composed of a linguistic term and its symbolic translation represented by a numeric value assessed in [-0.5,0.5) (Herrera & Martínez, 2000). This model manages linguistic information as a continuous rather than a discrete range, which provides more accurate results. The 2-tuple linguistic model excels over the other symbolic fuzzy-based models regarding precision and interpretability (Rodríguez et al., 2016). This model has been used to solve several kinds of linguistic decision-making issues in the actual world (Martinez et al., 2015). For instance, several authors have used it to model online customer reviews, obtaining more comprehensible results than those obtained using only numerical scales (Mi et al., 2014; Montes et al., 2015; Liu & Chen, 2018; Sohaib et al., 2019; Zhang et al., 2020a; Marín Díaz et al., 2021; Bueno et al., 2021).

The 2-tuple linguistic model represents linguistic information by a 2-tuple value (s_i, α), where $s_i \in S$ is a linguistic term, and $\alpha \in [-0.5, 0.5)$ is a numerical value that represents the distance to the central value of s_i. The definition is as follows.

Definition 1. Let $S = \{s_0, \ldots, s_g\}$ be a set of linguistic terms, and $\beta \in [0, g]$ be a value that represents the result of a symbolic aggregation operation, where $g + 1$ is the cardinality of S. The function $\Delta : [0, g] \rightarrow \langle S \rangle = Sx[-0.5, 0.5)$ is used to convert β into the 2-tuple value (s_i, α) as shown in Formula (1):

$$\Delta(\beta) = (s_i, \alpha), with \begin{cases} i = round(\beta) \\ \alpha = \beta - i,\ \alpha \in [-0.5, 0.5) \end{cases} \tag{1}$$

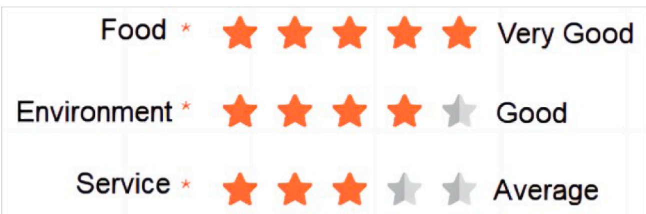

Fig. 3. Example of a user review in the Dianping.com database.

where *round(·)* is the rounding operation; s_i is the index label closest to β; and α is a numerical value of the symbolic translation.

This model can perform transformations between 2-tuple values and numerical values. The function Δ is bijective, its inverse function $\Delta^{-1}: \langle S \rangle = Sx[-0.5, 0.5) \rightarrow [0,\ g]$ converts the 2-tuple value into its equivalent numerical value as $\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$.

Example 1. The linguistic terms used by Dianping.com to evaluate restaurant criteria are *Very Poor* $= VP$, *Poor* $= P$, *Average* $= A$, *Good* $= G$, *Very Good* $= VG$. Therefore, $S = \{s_0 = VP,\ s_1 = P,\ s_2 = A,\ s_3 = G,\ s_4 = VG\}$ is a set of five linguistic terms used by Dianping.com, whose cardinality is $g + 1 = 5$ and whose definition is shown in Fig. 4.

Let $\beta = 2.3$ be a value representing the result of a symbolic aggregation operation on the set of linguistic terms $S = \{s_0 = VP,\ s_1 = P,\ s_2 = A,\ s_3 = G,\ s_4 = VG\}$. Then, its 2-tuple value is $\Delta(2.3) = (s_{round(2.3)}, 2.3 - round(2.3)) = (s_2, +0.3) = (A, +0.3)$. The inverse transformation is $\Delta^{-1}(s_2, +0.3) = 2 + 0.3 = 2.3$.

In the case that β equals 3, its 2-tuple value is $\Delta(3) = (s_3, 0) = (G, 0)$, which means that the difference between β and this linguistic term is zero ($\alpha = 0$). Adding a zero as a symbolic translation, $s_i \in S \rightarrow (s_i,\ 0)$, is identical to the label without symbolic translation (eg., $(G, 0) = G$). The two examples ($\beta = 2.3$ and $\beta = 3$) are shown in Fig. 5.

In addition, Herrera and Martínez introduced a way to perform a comparison between two 2-tuple linguistic values and the negation operator of a 2-tuple value, whose definitions are as follows.

Definition 2. The comparison of linguistic information represented by 2-tuple values is performed according to an ordinary lexicographic order (Herrera & Martínez, 2000). Let (s_M, α_1) and (s_L, α_2) be two 2-tuple values, the operator is generated to compare their linguistic 2-tuple values as the following:

- If $M<L$, (s_M, α_1) is smaller than (s_L, α_2) .
- If $M=L$, when:

  $\alpha_1 = \alpha_2$, (s_M, α_1) and (s_L, α_2) represent the same information.
  $\alpha_1 < \alpha_2$, (s_M, α_1) is smaller than (s_L, α_2).
  $\alpha_1 > \alpha_2$, (s_M, α_1) is larger than (s_L, α_2) .

- If $M>L$, (s_M, α_1) is larger than (s_L, α_2) .

Definition 3. The negation operator of a 2-tuple value is defined as Formula (2):

$$neg((s_i, \alpha)) = \Delta\left(g - \left(\Delta^{-1}(s_i, \alpha)\right)\right) = \Delta(g - \beta) \tag{2}$$

where $g+1$ is the cardinality of S, $S = \{s_0, \ldots, s_g\}$.

Since the 2-tuple linguistic model specifies the functions Δ and Δ^{-1} that convert numerical values into 2-tuple values and vice versa, any numerical aggregation operator can be easily adapted to cope with 2-tuple values. The arithmetic mean, the Weighted Average (WA) operator, and the OWA aggregation operator are three classical aggregation operators applied in the 2-tuple linguistic model (Herrera & Martínez, 2000). In this paper, the arithmetic mean and the OWA aggregation operator are applied to aggregate 2-tuple values. Definition 4 shows how to use the arithmetic mean to aggregate a set of 2-tuple values. The OWA aggregation operator is introduced in Section 3.3.

Definition 4. Let $X_k = \{(s_1, \alpha_1), (s_2, \alpha_2), \ldots, (s_n, \alpha_n)\}$ be a set of 2-tuple values of the kth criterion, whose arithmetic mean is calculated using Formula (3):

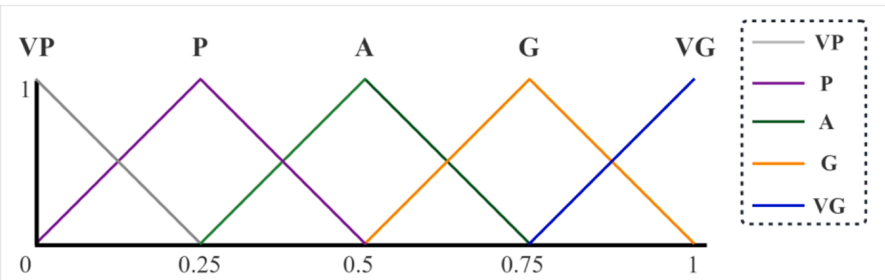

Fig. 4. Definition of the linguistic term set S at Dianping.com.

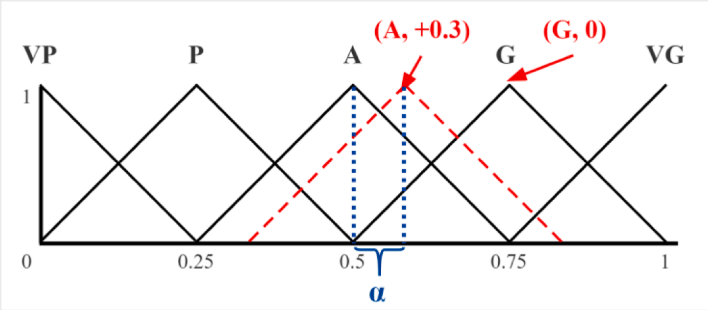

Fig. 5. Representation of examples of the 2-tuple values.

$$\overline{X_k} = \Delta\left(\frac{1}{n}\sum_{i=1}^{n}\Delta^{-1}(s_i,\alpha_i)\right) = \Delta\left(\frac{1}{n}\sum_{i=1}^{n}\beta_i\right) \tag{3}$$

where n is the number of users who have rated each restaurant criterion, $i = 1, \ldots, n$.

Example 2. Let $X_{service} = \{(A,0), (G,0), (G,0), (A,0), (A,0), (G,0), (A,0), (G,0), (A,0), (VG,0)\}$ be a set of 2-tuple values representing the ratings of ten users who evaluated the restaurant's service. With the function Δ^{-1}, this set can be converted into a set that includes their corresponding numeric values as $\Delta^{-1}(X_{service}) = \{2, 3, 3, 2, 2, 3, 2, 3, 2, 4\}$, whose arithmetic mean is 2.6. The 2-tuple value of its arithmetic mean is $\Delta(2.6) = (s_{round(2.6)}, 2.6 - round(2.6)) = (s_3, -0.4) = (G, -0.4)$. If the negation operator is applied to this 2-tuple value, it is computed as $neg((s_3, -0.4)) = \Delta(4 - (\Delta^{-1}(s_3, -0.4))) = \Delta(4 - (3 - 0.4)) = \Delta(1.4) = (s_1, +0.4) = (P, +0.4)$.

3.3. The Ordered Weighted Averaging (OWA) aggregation operator

The OWA aggregation operator was introduced by Yager (1988) as an information aggregation tool to address MCDM problems, which has been applied in many fields (Cho, 1995; Rinner & Malczewski, 2002; Torra, 2004; Li & Fei, 2019; Bueno et al., 2019; Wen et al., 2021; Shu, 2022). This aggregation operator is appropriate for modeling user attitudes (Serrano-Guerrero et al., 2022). In the OWA aggregation operator, the values of the variables are usually sorted in descending order beforehand (also called descending OWA (DOWA) aggregation operator). Another crucial issue is to determine the associated weights for each ordered value.

In the literature, several ways to determine the weights have been developed. Linguistic quantifiers (*At least one, Few, Half, Most, All*, etc.) can convey in a natural language different levels of user demand using formal mathematical formulas (Zadeh, 1996). By changing the linguistic quantifiers, the OWA aggregation operator can generate a wide range of decision strategies to express the decision-makers' attitudinal character in information aggregation (Yager, 1988; Peláez & Doña, 2003; Boroushaki & Malczewski, 2008; Ahn, 2010; Merigó et al., 2017; Kazemi-Beydokhti et al., 2019; Hao & Chiclana, 2020; Lakicevic & Srdjevic, 2022). Therefore, they have been employed in this paper to determine the weights associated with each ordered value.

Definitions 5 and 6 show the method applied to determine the weights. Other methods for calculating OWA weights are available in Xu (2005).

Table 2
Linguistic quantifiers and their corresponding λ parameters.

User demand levels	Linguistic quantifiers Q_q	λ
Extremely undemanding: users are satisfied with a restaurant when it has at least one positive review, even if the remaining reviews are negative, since they are extremely undemanding of this restaurant criterion.	Q_1 = *At least one*	0.0001
Very undemanding: users are satisfied with a restaurant when it has a few (more than one but not many) positive reviews, even if the remaining reviews are negative, since they are very undemanding of this restaurant criterion.	Q_2 = *Few*	0.1
Undemanding: users are satisfied with a restaurant when it has some positive reviews, since they are undemanding of this restaurant criterion.	Q_3 = *Some*	0.5
Neutral: users are satisfied with a restaurant when it has reviews that are, on average, positive, since they are neither too demanding nor undemanding of this restaurant criterion.	Q_4 = *Half*	1
Demanding: users are satisfied with a restaurant when it has many positive reviews, since they are demanding of this restaurant criterion.	Q_5 = *Many*	2
Very demanding: users are satisfied with a restaurant when it has mostly positive reviews, with very few unfavorable ones, since they are very demanding of this restaurant criterion.	Q_6 = *Most*	10
Extremely demanding: users are satisfied with a restaurant when it has no negative reviews, since they are very demanding of this restaurant criterion and are more concerned with the most unfavorable reviews.	Q_7 = *All*	1000

Definition 5. Regular increasing monotone (RIM) quantifiers can be applied to generate a parameterized subset in the unit interval (Yager, 1996), as shown in Formula (4):

$$Q_q(p) = p^{\lambda}, \lambda > 0 \tag{4}$$

where Q_q is a linguistic quantifier, represented as a fuzzy subset over the unit interval [0, 1]; for each p in the unit interval, the grade of membership $Q_q(p)$ indicates the compatibility of p with the concept denoted by Q_q.

Table 2 shows the levels of user demand defined in this paper, which represent the different preferences of users when viewing restaurant reviews. This is similar to the concept of degree of optimism based on the use of the OWA aggregation operator introduced by Filev and Yager (1995). For instance, when a user is more demanding of the service of a restaurant, they tend to focus more on negative reviews about it and has a less optimistic view of its service. In this case, more weights should be assigned to negative evaluations when aggregating various customer reviews for each restaurant criterion. This aggregation process taking into account the user demand levels can be achieved by using the ordered weights generated by the respective linguistic quantifier to aggregate the evaluations for each restaurant criterion. The corresponding linguistic quantifier for each user demand level, along with the parameters λ proposed by Boroushaki and Malczewski (2008) for each linguistic quantifier, are also shown in Table 2.

Definition 6. The ordered weights w_i ($w_i \in [0,\ 1]$) are calculated with Formula (5):

$$w_i = Q_q\left(\frac{i}{n}\right) - Q_q\left(\frac{i-1}{n}\right) = \left(\frac{i}{n}\right)^{\lambda} - \left(\frac{i-1}{n}\right)^{\lambda}, \lambda > 0 \tag{5}$$

where n is the number of users who have rated each restaurant criterion, $i = 1,\ \ldots,\ n$; and λ is the value associated with each linguistic quantifier Q_q. The higher λ is, the more demanding the user is. λ=1 indicates a medium level of demand (neither too demanding nor too undemanding).

The OWA aggregation operator is defined (Yager, 1988) as follows:

Definition 7. An OWA aggregation operator of dimension n is a mapping of $OWA: \ R^n \rightarrow R$, with an associated weighting vector W of dimension n, such that $\sum_{i=1}^{n} w_i = 1$ and $w_i \in [0,\ 1]$. The OWA for each linguistic quantifier is computed using Formula (6):

$$OWA_{Q_q}(a_1, a_2, \ldots a_n) = \sum_{i=1}^{n} w_i b_i \tag{6}$$

where $a_1, a_2,\ \ldots,\ a_n$ are the input values (i.e., user ratings); b_i is the ith largest element of the input values; Q_q is the linguistic quantifier; and w_i represents the ordered weights.

The 2LOWA aggregation operator is an extension of the OWA aggregation operator that can deal with 2-tuple values. The definition is as follows:

Definition 8. Let $X_k = \{(s_1, \alpha_1), (s_2, \alpha_2), \ldots, (s_n, \alpha_n)\}$ be a set of 2-tuple values of the kth criterion. A 2LOWA aggregation operator of dimension n is a mapping of 2LOWA: $R^n \rightarrow R$ with an associated weighting vector W of dimension n, such that $\sum_{i=1}^{n} w_i = 1$ and $w_i \in [0,\ 1]$. The 2LOWA for each linguistic quantifier is computed using Formula (7):

$$2LOWA_{Q_q}((s_1, \alpha_1), \ldots, (s_n, \alpha_n)) = \Delta\left(\sum_{i=1}^{n} w_i b_i\right) \tag{7}$$

where w_i represents the ordered weights; $b_i = \Delta^{-1}(s_i, \alpha_i)$.

Example 3. Take the set of $\Delta^{-1}(X_{service})$ from Example 2 and sort the values of it in descending order as {4, 3, 3, 3, 3, 2, 2, 2, 2, 2}. Using Formula (5), the weights for quantifier Q_1 ($\lambda = 0.0001$, and $n = 10$) are {0.9998, 0.0001, 0, 0, 0, 0, 0, 0, 0, 0}. Based on Formula (7), the 2-tuple value of this restaurant's service when using the quantifier Q_1 can be calculated as: $2LOWA_{Q_1}(X_{service}) = \Delta(4 * 0.9998 + 3 * 0.0001 + 0) = \Delta(3.9995) = (\text{VG}, \ -0.0005)$.

Table 3
Description of the degree of importance.

User demand levels	Degree of importance
Extremely undemanding	**Lowest importance:** the criterion being evaluated is not at all important to the user when calculating the overall score.
Very undemanding	**Very low importance:** the criterion being evaluated is not very important to the user when calculating the overall score.
Undemanding	**Low importance:** the criterion being evaluated is relatively unimportant to the user when calculating the overall score.
Neutral	**Moderate importance:** the criterion being evaluated is of some importance to the user when calculating the overall score.
Demanding	**High importance:** the criterion being evaluated is relatively important to the user when calculating the overall score.
Very demanding	**Very high importance:** the criterion being evaluated is very important to the user when calculating the overall score.
Extremely demanding	**Highest Importance:** the criterion being evaluated is the most important to the user when calculating the overall score.

Similarly, the 2-tuple value of this restaurant's service using the rest of the linguistic quantifiers are: $2LOWA_{Q_2}(X_{service}) = (\text{VG}, -0.2725)$, $2LOWA_{Q_3}(X_{service}) = (\text{G}, +0.0235)$, $2LOWA_{Q_4}(X_{service}) = (\text{G}, -0.4)$, $2LOWA_{Q_5}(X_{service}) = (\text{A}, +0.26)$, $2LOWA_{Q_6}(X_{service}) = (\text{A}, +0.001)$, and $2LOWA_{Q_7}(X_{service}) = (\text{A}, 0)$, respectively. The 2-tuple value calculated by quantifier Q_4 coincides with that calculated by the arithmetic mean in Example 2, which is $(\text{G}, -0.4)$. This indicates that when users have average demand for the restaurant's service, using the quantifier Q_4 to aggregate the ratings of different users is equivalent to using the arithmetic mean.

3.4. The Importance Weights (IW) method

In Section 3.3, it was explained that different levels of user demand could be expressed by means of linguistic quantifiers. In reality, if a user is more demanding of the restaurant's service, it also means that the level of the restaurant's service is more important to this user. Therefore, in order to achieve more accurate customized weights to compute the restaurant's overall score, this paper proposes to identify the degree of importance of various restaurant criteria according to the level of user demand. Table 3 shows the degree of importance corresponding to the level of user demand and its description.

According to Table 3, the set of linguistic terms used to express the degree of importance can be defined as $DI = \{di_0 = Lowest = LWST,\ di_1 = Very\ Low = VL,\ di_2 = Low = L,\ di_3 = Moderate = M,\ di_4 = High = H,\ di_5 = Very\ High = VH,\ di_6 = Highest = HIST\}$, whose cardinality is $g + 1 = 7$. Fig. 6 shows the set of linguistic terms with seven labels to indicate the degree of importance.

The IW method is defined as follows:

Definition 9. The weight of the kth criterion is calculated using Formula (8):

$$w_k = \frac{\Delta^{-1}(di_k, \alpha_k)}{\sum_{k=1}^{m} \Delta^{-1}(di_k, \alpha_k)} \tag{8}$$

where (di_k, α_k) is a 2-tuple value representing the degree of importance corresponding to the kth criterion's user demand level. If the user is extremely demanding of the restaurant's service, $(di_{Service}, \alpha_{Service}) = (HIST, 0)$.

Definition 10. Let $V = \{(s_1, \alpha_1), (s_2, \alpha_2), \ldots, (s_m, \alpha_m)\}$ be a set of ratings expressed in 2-tuple values for m criteria, and $LI = \{(di_1, \alpha_1), \ldots, (di_m, \alpha_m)\}$ be a vector of 2-tuple values corresponding to the degree of importance associated with each value in V. The overall score for each restaurant is determined by Formula (9):

$$Score = \Delta\left(\sum_{k=1}^{m} \Delta^{-1}(s_k, \alpha_k) \cdot w_k\right) = \Delta\left(\frac{\sum_{k=1}^{m} \Delta^{-1}(s_k, \alpha_k) \cdot \Delta^{-1}(di_k, \alpha_k)}{\sum_{k=1}^{m} \Delta^{-1}(di_k, \alpha_k)}\right) \tag{9}$$

where (s_k, α_k) represents the rating of the kth criterion obtained by Formula (7), $k=1,2,\ldots,m$. If $(di_1,\alpha_1) = (di_2,\alpha_2) = \ldots = (di_k,\alpha_k)$, these m criteria have the same importance.

Example 4. Suppose that user A is extremely demanding of the restaurant's service, food, and environment, so the vector of 2-tuple values corresponding to the degree of importance associated with these three restaurant criteria is $LI_A = \{(HIST, 0), (HIST, 0), (HIST, 0)\}$. The ratings of service, food, and environment of the three restaurants calculated by Formula (7) using the quantifier Q_7 are shown in Table 4.

The overall score for restaurant 1 is calculated as follows:

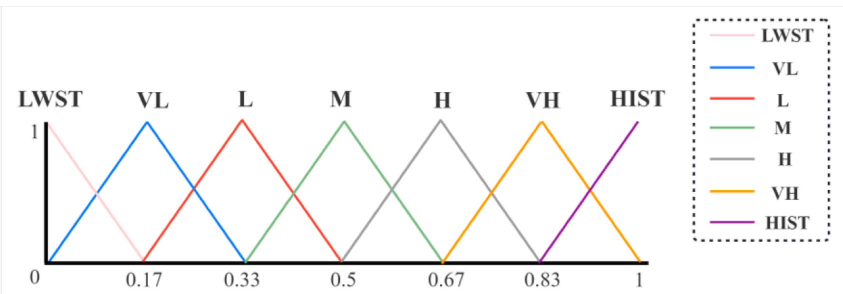

Fig. 6. Definition of linguistic term set *DI*.

Table 4
Restaurant ratings expressed in 2-tuple values (User A).

Restaurant	Service	Food	Environment
1	(P, +0.12)	(G, +0.20)	(A, +0.05)
2	(A, +0.10)	(P, +0.20)	(G, -0.08)
3	(A, -0.10)	(G, +0.06)	(A, -0.15)

Table 5
Restaurant ratings expressed in 2-tuple values (User B).

Restaurant	Service	Food	Environment
1	(A, +0.11)	(G, +0.20)	(G, +0.10)
2	(G, +0.08)	(P, +0.20)	(VG, -0.12)
3	(G, -0.20)	(G, +0.06)	(G, -0.21)

$$
\begin{aligned}
Score_1 &= \Delta\left(\frac{\Delta^{-1}(P,+0.12)\cdot\Delta^{-1}(HIST,0)+\Delta^{-1}(G,+0.2)\cdot\Delta^{-1}(HIST,0)+\Delta^{-1}(A,+0.05)\cdot\Delta^{-1}(HIST,0)}{\Delta^{-1}(HIST,0)+\Delta^{-1}(HIST,0)+\Delta^{-1}(HIST,0)}\right)\\
&= \Delta\left(\frac{1.12\cdot 6+3.2\cdot 6+2.05\cdot 6}{6+6+6}\right) = \Delta(2.123) = (A,+0.123)
\end{aligned}
$$

Similarly, the overall scores for restaurants 2 and 3 are $Score_2 = (A, +0.073)$, and $Score_3 = (A, +0.27)$. Since $Score_3 > Score_1 > Score_2$, user A will choose Restaurant 3.

If user B is extremely demanding of the restaurant's food, but is undemanding of the restaurant's service and environment, the vector of 2-tuple values corresponding to the degree of importance associated with these three restaurant criteria is $LI_B = \{(L,0),(HIST,0),(L,0)\}$. The ratings of service, food, and environment of the three restaurants are shown in Table 5.

The difference between Table 4 and Table 5 is that the ratings of restaurant service and environment are different, as the level of

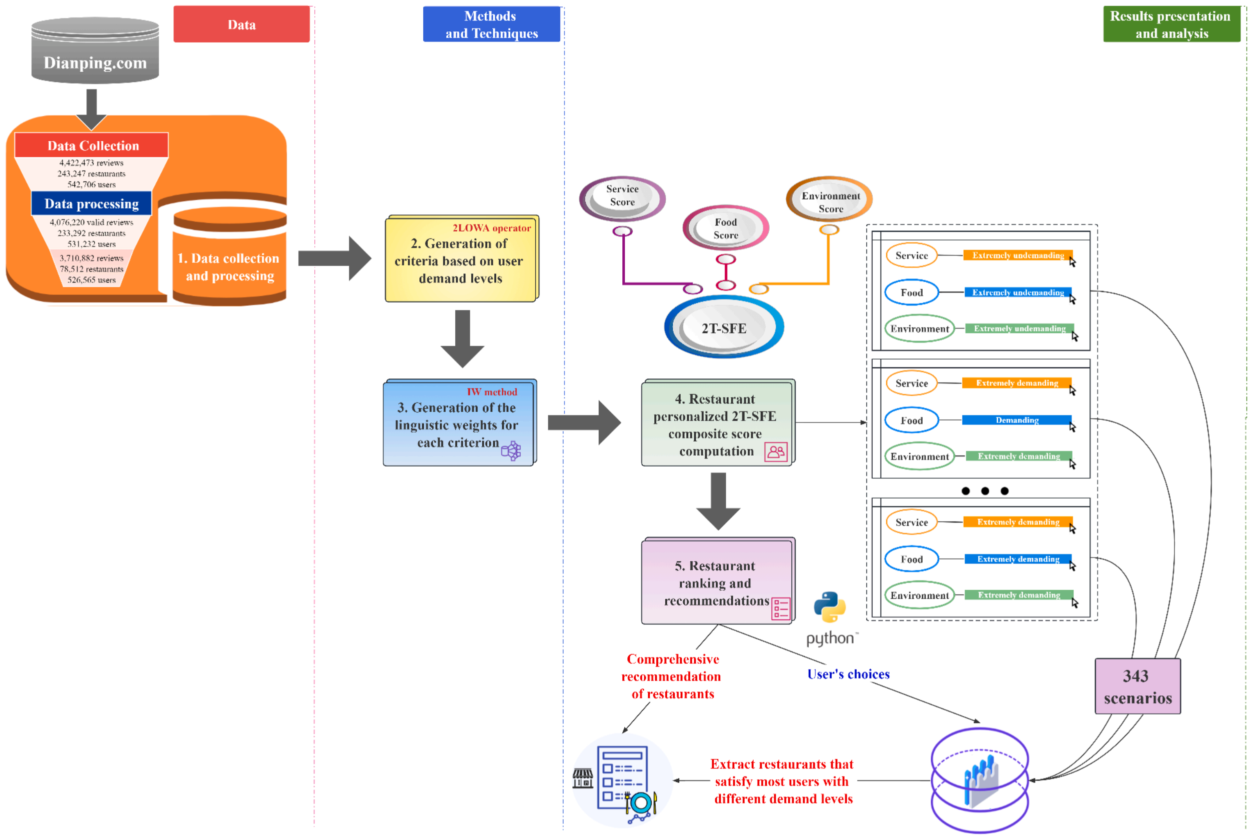

Fig. 7. Proposed model for restaurant ranking and selection.

user demand for these two criteria has changed from "extremely demanding" to "undemanding". For user B, the overall scores for these three restaurants are $Score_1 = (G, -0.038)$, $Score_2 = (A, +0.112)$, and $Score_3 = (G, -0.046)$, respectively. Since $Score_1 > Score_3 > Score_2$, user B will choose Restaurant 1.

4. Proposed model

The proposed model is composed of five steps: section 4.1 shows the process of collecting and cleaning the dataset; section 4.2 shows the process of extracting useful information from the dataset, and aggregating it into new criteria reflecting different levels of user demand of restaurant service, food, and environment; section 4.3 presents how to generate diverse scenarios of the linguistic weights for each new criterion; section 4.4 calculates the customized composite score of the restaurant based on user demand levels of restaurant service, food, and environment; section 4.5 shows the results of restaurant ranking and recommendations. Fig. 7 shows each step in the proposed model, corresponding to the structure introduced in Fig. 1.

4.1. Data collection and processing

This step obtains online reviews of Chinese restaurants from Dianping.com. Like many other review sites, Dianping.com uses a five-star rating system and linguistic terms to express users' reviews of various restaurant aspects (see Fig. 3). As shown in Fig. 3, the rating scale employed by Dianping.com is as follows: "1 star=*Very Poor*, 2 stars=*Poor*, 3 stars=*Average*, 4 stars=*Good*, and 5 stars=*Very Good*".

This paper uses the dataset published by Zhang (2013), a collection of user reviews about restaurants collected from Dianping.com between April 7, 2003, and February 8, 2012. This dataset comprises more than 4.4 million reviews from 542,706 users on 243,247 restaurants. Each review contains ratings the user gives (ranging from 1 to 5 stars) for three criteria (Service, Food, and Environment) to evaluate the restaurants. It also includes the review date, user ID, and restaurant ID.

When performing data processing, considering user reviews with missing partial dimensional ratings would be considered spam or intentionally bad reviews on Dianping.com (see Section 3.1), only those restaurants that have received valid reviews with all three criteria (*Service, Food*, and *Environment*) are included in this study. It results in a new dataset of 233,292 restaurants with 4,076,220 reviews from 531,232 users. However, only 78,512 of the 233,292 restaurants in the new dataset received no less than ten reviews, which is the minimum requirement for Dianping.com to start calculating the restaurant's overall rating. Therefore, this paper only analyses these 78,512 restaurants that appeared in the list of user-recommended restaurants and were given overall scores by the algorithm.

Let $T = \{t_1, ..., t_{\#T}\}$ be the set of restaurants, and $C = \{Service, \ Food, Environment\}$ be the set of restaurant criteria evaluated by users $U = \{u_1, ..., u_{\#U}\}$ on Dianping.com. The number of user reviews received by each restaurant is different, so the set of users associated with each restaurant can be expressed as $U^1 = \{u_1^1, ..., u_{\#U^1}^1\}$, $U^2 = \{u_1^2, ..., u_{\#U^2}^2\}, ..., U^{\#T} = \{u_1^{\#T}, ..., u_{\#U^{\#T}}^{\#T}\}$, with $U^1, U^2, ..., U^{\#T} \subseteq U$.

Thus, a processed dataset $TA = \{(t_1, \{(u_1^1, d_1^1, \ v_1^{Service_1}, \ v_1^{Food_1}, v_1^{Environment_1}), \cdots, (u_{\#U^1}^1, d_{\#U^1}^1, \ v_{\#U^1}^{Service_1}, \ v_{\#U^1}^{Food_1}, v_{\#U^1}^{Environment_1})\}), ..., (t_{\#T}, \{(u_1^{\#T}, d_1^{\#T}, \ v_1^{Service_{\#T}}, \ v_1^{Food_{\#T}}, \ v_1^{Environment_{\#T}}), ..., (u_{\#U^{\#T}}^{\#T}, d_{\#U^{\#T}}^{\#T}, \ v_{\#U^{\#T}}^{Service_{\#T}}, \ v_{\#U^{\#T}}^{Food_{\#T}}, \ v_{\#U^{\#T}}^{Environment_{\#T}})\})\}$ is obtained, where:

- t_f: is the identifying code of each restaurant, with $t_f \in T$ and $f = 1, ..., \#T$.

Table 6
Reviews received by the restaurant t_{32519}.

t_f	u_i^f	d_i^f (YYYY − MM − DD)	$v_i^{Service_f}$	$v_i^{Food_f}$	$v_i^{Environment_f}$
32519	37602	2006-10-11	A	A	A
32519	83244	2008-02-05	A	G	VG
32519	77755	2008-07-02	G	A	A
32519	115294	2008-09-19	VG	G	G
32519	77764	2008-09-19	A	P	P
32519	222219	2008-12-12	A	A	A
32519	37615	2009-05-11	G	A	G
32519	37630	2009-05-26	A	P	A
32519	200053	2009-12-03	G	G	G
32519	222220	2010-04-01	A	A	A
32519	83986	2010-05-03	VG	A	VG
32519	222221	2010-07-07	A	P	A
32519	1891	2011-01-13	A	A	A
32519	77779	2011-03-14	VG	A	A
32519	222222	2012-01-30	G	A	G

- u_i^f: is the identifying code of each user, which is used to distinguish the user reviews received by each restaurant t_f, with $i = 1, \ldots, \#U$, $f = 1, \ldots, \#T$, and $u_i^f \in U$.
- d_i^f: is the date on which the user u_i^f evaluated the restaurant t_f, $d_i^f \in d$. d is the analysis period delimited by the start date $d_s = April\ 7,\ 2003$ and the end date $d_e = February\ 8,\ 2012$.
- $(v_i^{Service_f},\ v_i^{Food_f}, v_i^{Environment_f})$: are the ratings of service, food, and environment for each restaurant expressed on a linguistic scale, where $i = 1, \ldots, \#U$ and $f = 1, \ldots, \#T$. According to the rating scale on Dianping.com, the linguistic scale contains five values: "*Very Poor*=*VP*", "*Poor*=*P*", "*Average*=*A*", "*Good*=*G*", and "*Very Good*=*VG*". These linguistic values are symmetrical, whose central value is neutral (i.e., "*Average*") (Tao et al., 2014; Marín Díaz et al., 2021; Bueno et al., 2022). They are modeled by fuzzy triangular labels $(v_{\#U}^{\#C_{\#T}} \in S)$, as shown in Fig. 4.

Table 6 shows an example of a restaurant from the dataset *TA*, which received more than ten reviews.

4.2. Generation of criteria based on user demand levels

Dianping.com uses the ratings of service, food, and environment to update the overall star rating of the restaurant. This step generates new criteria that reflect the different levels of user demand for these three aspects of the restaurant.

The seven linguistic quantifiers of the 2LOWA aggregation operator are applied to each of the three restaurant aspects, resulting in the creation of 21 new criteria to reflect the varying levels of user demand for restaurant service, food, and environment. Utilizing the newly generated criteria, a new dataset is created as:

$$TA\_2LOWA = \left\{ \begin{array}{c} (t_1,\ (O_{Q_1}^{Service_1}, \ldots, O_{Q_7}^{Service_1}), (O_{Q_1}^{Food_1}, \ldots, O_{Q_7}^{Food_1}), (O_{Q_1}^{Environment_1}, \ldots, O_{Q_7}^{Environment_1})), \\ \cdot \\ \cdot \\ \cdot \\ (t_{\#T},\ (O_{Q_1}^{Service_{\#T}}, \ldots, O_{Q_7}^{Service_{\#T}}), (O_{Q_1}^{Food_{\#T}}, \ldots, O_{Q_7}^{Food_{\#T}}), (O_{Q_1}^{Environment_{\#T}}, \ldots, O_{Q_7}^{Environment_{\#T}})) \end{array} \right\} \text{ where:}$$

- t_f: is the identifying code of each restaurant, with $t_f \in T$ and $f = 1, \ldots, \#T$.
- $\{(O_{Q_1}^{Service_f}, \ldots, O_{Q_7}^{Service_f}), (O_{Q_1}^{Food_f}, \ldots, O_{Q_7}^{Food_f}), (O_{Q_1}^{Environment_f}, \ldots, O_{Q_7}^{Environment_f})\}$: are the linguistic ratings aggregated by the 2LOWA aggregation operator with seven linguistic quantifiers for service, food, and environment of each restaurant t_f, $O_{Q_q}^{Service_f} \in Sx[-0.5,\ 0.5)$. $O_{Q_q}^{Service_f} = 2LOWA_{Q_q}(v_1^{Service_f}, \ldots,\ v_i^{Service_f})$, with $i = 1, \ldots, \#U; f = 1, \ldots, \#T$; Q_q represents linguistic quantifiers defined in Table 2; $2LOWA_{Q_q}(\cdot)$ has been defined in Formula (7). Both $O_{Q_q}^{Food_f}$ and $O_{Q_q}^{Environment_f}$ belong to $Sx[-0.5,\ 0.5)$, and the formula used to calculate their 2-tuple values is $2LOWA_{Q_q}(\cdot)$.

Table 7 shows the 21 new criteria generated to reflect the different levels of user demand for the service, food, and environment of restaurant t_{32519}.

To compare with this newly generated dataset *TA_2LOWA*, the arithmetic mean score dataset *TA_MEAN* is generated as: $TA\_MEAN = \{(t_1,\ M^{Service_1}, M^{Food_1},\ M^{Environment_1}),\ \ldots, (t_{\#T},\ M^{Service_{\#T}}, M^{Food_{\#T}},\ M^{Environment_{\#T}})\}$, where t_f is the same as that defined in the dataset *TA_2LOWA*; $(M^{Service_f}, M^{Food_f}, M^{Environment_f})$ are the average ratings expressed in 2-tuple values for service, food, and environment of each restaurant, with $M^{Service_f} = \overline{X_k}(v_1^{Service_f}, \ldots,\ v_i^{Service_f})$, $M^{Food_f} = \overline{X_k}(v_1^{Food_f}, \ldots,\ v_i^{Food_f})$, $M^{Environment_f} = \overline{X_k}(v_1^{Environment_f}, \ldots,\ v_i^{Environment_f})$, $i = 1, \ldots, \#U;\ f = 1, \ldots, \#T$; $\overline{X_k}(\cdot)$ has been defined in Formula (3). Table 8 shows an example of the dataset *TA_MEAN*.

4.3. Generation of the linguistic weights for each criterion

This step generates diverse scenarios of the weights for each criterion produced in the previous step. A total of 343 (i.e., 7 × 7 ×

Table 7
21 new criteria generated for restaurant t_{32519}.

t_f	$O_{Q_1}^{Service_f}$	$O_{Q_2}^{Service_f}$	$O_{Q_3}^{Service_f}$	$O_{Q_4}^{Service_f}$	$O_{Q_5}^{Service_f}$	$O_{Q_6}^{Service_f}$	$O_{Q_7}^{Service_f}$
32519	(VG, -0.0010)	(VG, -0.2218)	(G, +0.1307)	(G, -0.3315)	(A, +0.2573)	(A, +0.0005)	A
t_f	$O_{Q_1}^{Food_f}$	$O_{Q_2}^{Food_f}$	$O_{Q_3}^{Food_f}$	$O_{Q_4}^{Food_f}$	$O_{Q_5}^{Food_f}$	$O_{Q_6}^{Food_f}$	$O_{Q_7}^{Food_f}$
32519	(G, -0.0008)	(G, -0.1705)	(A, +0.3420)	(A, +0.0015)	(A, -0.3204)	(P, +0.1074)	P
t_f	$O_{Q_1}^{Environment_f}$	$O_{Q_2}^{Environment_f}$	$O_{Q_3}^{Environment_f}$	$O_{Q_4}^{Environment_f}$	$O_{Q_5}^{Environment_f}$	$O_{Q_6}^{Environment_f}$	$O_{Q_7}^{Environment_f}$
32519	(VG, -0.0010)	(VG, -0.2767)	(G, -0.0360)	(A, +0.4684)	(A, +0.0484)	(A, -0.4983)	P

Table 8
The data of the restaurant t_{32519} in the dataset *TA_MEAN*.

t_f	$M^{Service_f}$	M^{Food_f}	$M^{Environment_f}$
32519	(G, -0.3332)	A	(A, +0.4668)

Table 9
Examples of weight scenarios for the restaurants on Dianping.com.

Scenario id	Scenario description	Input variables	Service	Food	Environment
$Scenario_1$	Users are extremely demanding of restaurant service, food, and environment.	$O_{Q_7}^{Service_f}, O_{Q_7}^{Food_f}, O_{Q_7}^{Environment_f}$	33.33%	33.33%	33.33%
$Scenario_2$	Users are very demanding of restaurant service, but undemanding of the food and environment.	$O_{Q_6}^{Service_f}, O_{Q_3}^{Food_f}, O_{Q_3}^{Environment_f}$	55.56%	22.22%	22.22%
$Scenario_3$	Users are neutral about restaurant food and environment, but demanding of the service.	$O_{Q_5}^{Service_f}, O_{Q_4}^{Food_f}, O_{Q_4}^{Environment_f}$	40%	30%	30%
$Scenario_4$	Users are neutral (neither too demanding nor undemanding) about restaurant service, food, and environment.	$O_{Q_4}^{Service_f}, O_{Q_4}^{Food_f}, O_{Q_4}^{Environment_f}$	33.33%	33.33%	33.33%
$Scenario_5$	Users are very undemanding of restaurant service, food, and environment.	$O_{Q_2}^{Service_f}, O_{Q_2}^{Food_f}, O_{2}^{Environment_f}$	33.33%	33.33%	33.33%
$Scenario_6$	Users are extremely demanding of restaurant environment, demanding of restaurant food, and undemanding of restaurant service.	$O_{Q_3}^{Service_f}, O_{Q_5}^{Food_f}, O_{Q_7}^{Environment_f}$	16.67%	33.33%	50%
$Scenario_7$	Users are extremely undemanding of restaurant service, but demanding of the food and environment.	$O_{Q_1}^{Service_f}, O_{Q_5}^{Food_f}, O_{Q_5}^{Environment_f}$	0%	50%	50%
$Scenario_8$	Users are extremely undemanding of restaurant service, food, and environment.[1]	$O_{Q_1}^{Service_f}, O_{Q_1}^{Food_f}, O_{Q_1}^{Environment_f}$	0%	0%	0%
$Scenario_{Mean}$	Users have average demand of restaurant service, food, and environment.	$M^{Service_f}$, M^{Food_f}, $M^{Environment_f}$	33.33%	33.33%	33.33%

[1] If users are extremely undemanding of restaurant service, food, and environment, none of these three criteria is considered important when selecting a restaurant. In such a case, restaurants would be randomly recommended to users.

$7 = 7^3$) possible weight scenarios are obtained using Formula (8). Table 9 shows some of the 343 weight scenarios obtained for the dataset *TA_2LOWA*, and the scenario of the weights for the dataset *TA_MEAN*.

As shown in Table 9, when users have the same level of demand for restaurant service, food, and environment— whether they are extremely demanding or undemanding—these three criteria are considered equally important in their restaurant selection and thus have the same weights.

However, even though the weight distribution in some scenarios coincides with the one derived using the arithmetic mean, it does not mean that the overall scores of the restaurants are also the same. This is because the values of the new criteria generated by various linguistic quantifiers differ from those of the *TA_MEAN*. Only when the user demand for restaurant service, food, and environment is at a moderate level are the restaurant's overall score and the weights of each restaurant criterion the same as those calculated by the

Table 10
Composite score results for the restaurant t_{32519}.

	Scenario for User A			Scenario for User B		
	Data	Weight	Data x Weight	Data	Weight	Data x Weight
Service	$\Delta^{-1}((VG, -0.0010)) = 3.999$	0%	0	$\Delta^{-1}((A)) = 2$	33.33%	0.6666
Food	$\Delta^{-1}((A, -0.3204)) = 1.6796$	50%	0.8398	$\Delta^{-1}((P)) = 1$	33.33%	0.3333
Environment	$\Delta^{-1}((A, +0.0484)) = 2.0484$	50%	1.0242	$\Delta^{-1}((P)) = 1$	33.33%	0.3333
Composite Score	$\Delta(1.864) = (A, -0.136)$			$\Delta(1.3332) = (P, +0.3332)$		

Table 11
Top 10 restaurants on Dianping.com under eight diverse scenarios.

R	*Scenario*$_1$		*Scenario*$_2$		*Scenario*$_3$		*Scenario*$_4$		*Scenario*$_5$		*Scenario*$_6$		*Scenario*$_7$		*Scenario*$_{Mean}$	
	t_f	*Composite Score*	t_f	*Composite Score*	t_f	*Composite Score*	t_f	*Composite Score*	t_f	*Composite Score*	t_f	*Composite Score*	t_f	*Composite Score*	t_f	*Composite Score*
1	55765	(G,+0.3332)	55765	(VG,-0.4472)	55765	(VG,-0.2052)	169535	(VG,-0.1552)	169535	(VG,-0.0168)	55765	(G,+0.4892)	169535	(VG,-0.2836)	169535	(VG, -0.1540)
2	235986*	(G,+0.3332)	169535	(VG,-0.4864)	169535	(VG,-0.2064)	55765	(VG,-0.1688)	55765	(VG,-0.0204)	111613	(G,+0.4840)	55765	(VG,-0.3092)	55765	(VG,-0.1668)
3	224393*	(G,+0.3332)	224393	(G,+0.4540)	224393	(VG,-0.2640)	224393	(VG,-0.2000)	224393	(VG,-0.0236)	224393	(G,+0.4824)	224393	(VG,-0.3200)	224393	(VG,-0.2000)
4	111613*	(G,+0.3332)	232652	(G,+0.4360)	28868	(VG,-0.2880)	28868	(VG,-0.2432)	28868	(VG,-0.0284)	27486	(G,+0.4756)	210784	(VG,-0.4016)	28868	(VG,-0.2432)
5	120560*	(G,+0.3332)	27486	(G,+0.4108)	232652	(VG,-0.3232)	232652	(VG,-0.2732)	196652	(VG,-0.0292)	118253	(G,+0.4724)	74395	(VG,-0.4120)	74395	(VG,-0.2692)
6	169535	G	111613	(G,+0.3916)	117698	(VG,-0.3368)	74395	(VG,-0.2768)	210158	(VG,-0.0304)	120560	(G,+0.4716)	118253	(VG,-0.4408)	232652	(VG,-0.2728)
7	27486*	G	210784	(G,+0.3908)	27486	(VG,-0.3516)	117698*	(VG,-0.2768)	74395	(VG,-0.0308)	57877	(G,+0.4452)	235986	(VG,-0.4492)	196652	(VG,-0.2752)
8	118253*	G	149066	(G,+0.3876)	196652	(VG,-0.3572)	210158	(VG,-0.2796)	117698	(VG,-0.0312)	235986	(G,+0.4416)	28868	(VG,-0.4588)	210158	(VG,-0.2780)
9	232652*	G	117698	(G,+0.3840)	27865	(VG,-0.3580)	196652	(VG,-0.2940)	175441	(VG,-0.0332)	232652	(G,+0.4264)	120560	(VG,-0.4688)	117698	(VG,-0.2788)
10	57877*	G	139963	(G,+0.3804)	210158	(VG,-0.3624)	27865	(VG,-0.3008)	27865	(VG,-0.0344)	29244	(G,+0.4228)	27486	(VG,-0.4756)	27865	(VG,-0.2888)

[*] This restaurant is ranked the same as the previous one, as they have the same composite scores. For example, in *Scenario*$_4$, as restaurants 74395 and 117698 have the same 2-tuple scores, higher than restaurant 210158, they are ranked 6th, 6th, and 8th, respectively.

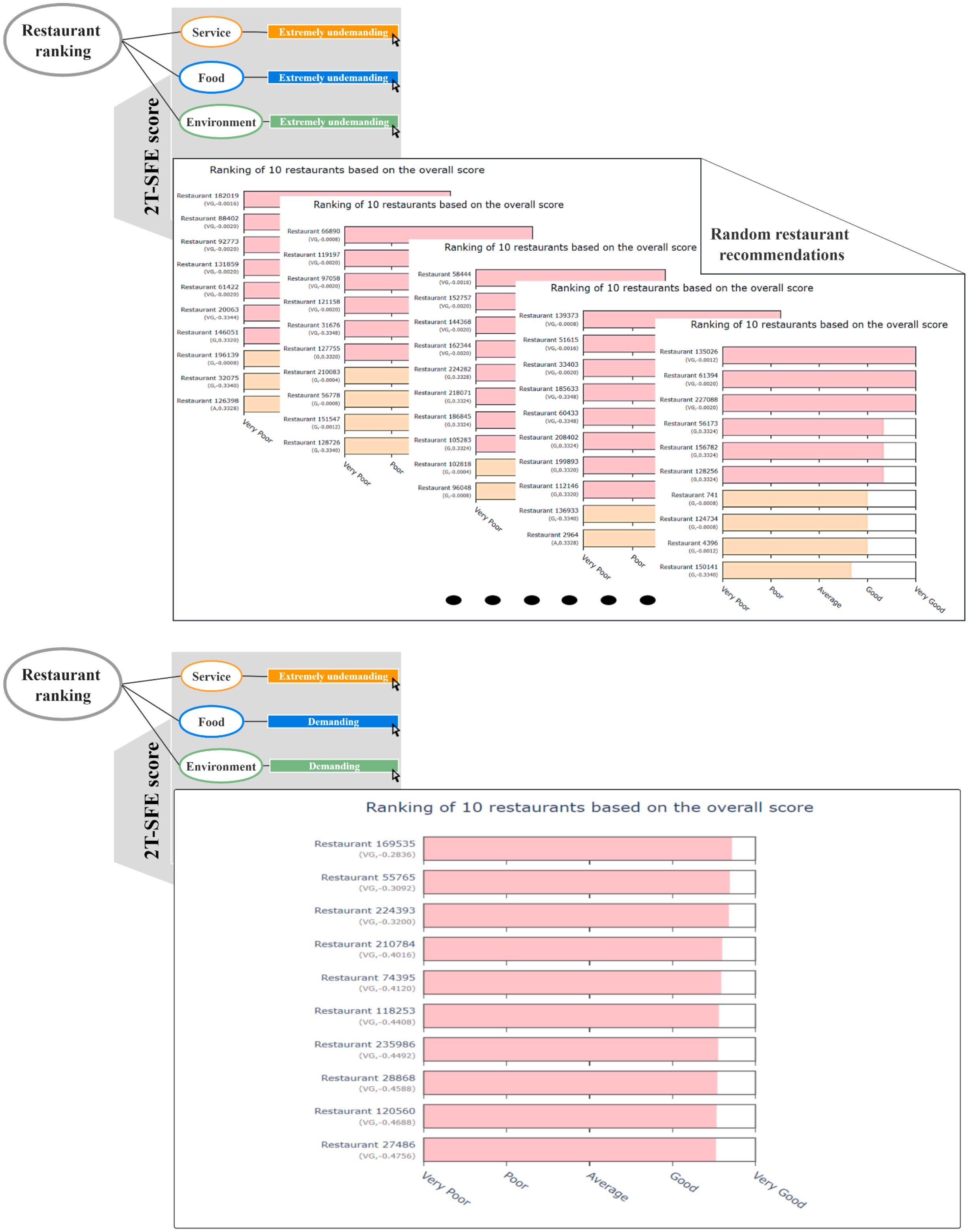

Fig. 8. Examples of the top 10 restaurants under *Scenario*$_7$ and *Scenario*$_8$.

arithmetic mean. The new criteria generated by quantifier Q_4 for restaurant service, food, and environment are essentially identical to those calculated using the arithmetic mean, with only slight decimal differences, as evident in the examples provided in Tables 7 and 8.

4.4. Restaurant personalized 2T-SFE composite score computation

Based on the 343 different weight scenarios obtained in the previous step, this step generates customized 2T-SFE composite scores for 78,512 restaurants. A total of 343 composite scoring schemes are obtained using Formula (9). For example, user A is extremely undemanding of restaurant service, but demanding of the food and environment. User B is extremely demanding of these three restaurant criteria. Table 10 shows the process and results of the composite score calculation for the restaurant t_{32519} in the two scenarios mentioned above.

As shown in Table 10, despite restaurant t_{32519} having very good service, for user A, its composite score indicates that the establishment falls slightly below the average level among the 78,512 restaurants, making it less desirable for user A to select it. Regarding user B, this restaurant will never be included in the consideration list. In fact, the process of selecting a restaurant could be further facilitated by combining it with the ranking of the restaurants, which will be discussed in the next step.

4.5. Restaurant ranking and recommendations.

In this step, the 78,512 restaurants are ranked based on the previously obtained comprehensive scores, and the results are showcased in an interactive application created using the Python programming language. This allows users to visualize the restaurant list and effortlessly select a restaurant that aligns with their needs. Additionally, the platform can make more accurate and satisfying recommendations for users.

Table 11 shows the IDs of the top 10 restaurants and their corresponding overall scores for the scenarios presented in Table 9, except for *Scenario*$_8$. *Scenario*$_8$ is not included in Table 11 because, in this case, none of the three restaurant aspects (*Service, Food*, and *Environment*) is deemed important when selecting a restaurant. The restaurants will be randomly recommended in this situation. Fig. 8 presents screenshot examples of the top 10 restaurants according to *Scenario*$_8$ in the interactive application, along with the top 10 restaurants according to *Scenario*$_7$. As shown in Fig. 8, in the case of *Scenario*$_8$, these top 10 restaurants are not fixed but appear randomly. In contrast, in *Scenario*$_7$, they are fixed and match the list of the top 10 restaurants in Table 11.

In addition, Table 12 shows the 92 restaurants that rank in the top 10, as well as their respective frequencies of appearance, except

Table 12
Frequency list of the restaurant appearance in the top 10 across 342 scenarios.

t_f	Frequency of appearance in the top 10		t_f	Frequency of appearance in the top 10		t_f	Frequency of appearance in the top 10	
	frequency	%		frequency	%		frequency	%
55765	335	97.95	80065	17	4.97	121080	1	0.29
224393	325	95.03	27865	16	4.68	195681		
169535	262	76.61	83552	15	4.39	117389		
111613	246	71.93	89383	13	3.80	62007		
27486	225	65.79	54807	12	3.51	116309		
120560	200	58.48	139827			96804		
232652	194	56.73	180524	10	2.92	68287		
235986	168	49.12	23295	9	2.63	215217		
118253	159	46.49	207649			175427		
149066	150	43.86	179699	8	2.34	139581		
57877	136	39.77	80969			213001		
210784			231714			19407		
28868	94	27.49	26758	7	2.05	206372		
240650	81	23.68	209761			2211		
32073	71	20.76	162567			223491		
117698	59	17.25	141881	6	1.75	179840		
29244	58	16.96	209530	5	1.46	105940		
137778	56	16.37	181266			141479		
175441	47	13.74	197815	4	1.17	138070		
74395	43	12.57	18795	3	0.88	208508		
85881	36	10.53	18570			112002		
110358	33	9.65	85483			239926		
139963			52134			141544		
210158	30	8.77	27423			210426		
57349	28	8.19	168664			237073		
172635	27	7.89	155851			240107		
196652	26	7.60	83940			25213		
171960	23	6.73	201088			183514		
200002			50850			147349		
145920	22	6.43	1290	1	0.29	3756		
65112	21	6.14	70498					

for the extreme case where restaurants will be randomly recommended to users (i.e., $Scenario_8$). The analytical details of Tables 11 and 12 are described in Section 5.

5. Analysis of results and comparison

This section analyzes the results of the restaurant rankings produced by the proposed model. As shown in Table 11, when users have a medium level of demand of restaurant service, food, and environment (i.e., $Scenario_4$, all linguistic ratings are aggregated using the quantifier Q_4), most of the results for $Scenario_4$ and $Scenario_{Mean}$ are the same. The ranking of the top ten restaurants is almost identical, except for a slight decimal difference in their 2-tuple values.

However, there are differences in restaurant ranking when comparing other scenarios. For example, when comparing $Scenario_3$ and $Scenario_4$, it can be observed that the ranking of the restaurant changes if the degree of user demand of restaurant service increases, even though the level of user demand of restaurant food and environment is constant. In particular, restaurant 27486 was not in the top 10 in $Scenario_4$, but ranked seventh in $Scenario_3$. In $Scenario_4$, restaurant 74395 ranked sixth; however, it was not among the top ten in $Scenario_3$.

Similarly, the rankings of the top 10 restaurants change significantly when the level of user demand changes dramatically. For instance, in $Scenario_5$, none of the restaurants that appear in the top 10 are present in the top 10 of $Scenario_1$, except for restaurants 55765, 224393, and 169535 (these three restaurants have a high frequency of appearance in the top 10; see Table 12). This shows that the ranking of some restaurants decreases as users become more demanding of the restaurant service, food, and environment, as they fail to meet the high level of user demand.

In addition, Table 12 shows that several restaurants regularly appear in the top 10 under 342 scenarios, such as restaurants 55765, 224393, 169535, and 111613, with a frequency of over 70%. Since they frequently appear in the top 10, these four restaurants on Dianping.com can satisfy the requirements of most users with different levels of demand of service, food, and environment. However, some restaurants have less than 1% frequency of appearance in the top 10.

The Cox-Stuart test (COX & STUART, 1955) has been used in this paper to assess the trend (increasing, decreasing, or stable) of restaurant rankings that change with user demand levels, as it is particularly robust for trend analysis. Since a lower number indicates a higher ranking (e.g., 1 means it ranks first), if the Cox-Stuart result indicates a decreasing trend (e.g., from 1000 to 1), the restaurant is ranked higher as users are more demanding of restaurant criteria. Table 13 shows the trend of change in the ranking of the 92

Table 13
Ranking changes of 92 restaurants.

t_f	Cox-Stuart result	Average ranking	t_f	Cox-Stuart result	Average ranking	t_f	Cox-Stuart result	Average ranking
55765	stable[1]	2	80065	decreasing[2]	54	121080	decreasing[2]	64
224393	stable[1]	4	27865	increasing[3]	5572	195681	decreasing[2]	250
169535	stable[1]	7	83552	increasing[3]	199	117389	decreasing[2]	241
111613	decreasing[2]	24	89383	decreasing[2]	47	62007	decreasing[2]	5145
27486	decreasing[2]	18	54807	decreasing[2]	245	116309	decreasing[2]	80
120560	decreasing[2]	23	139827	decreasing[2]	88	96804	decreasing[2]	102
232652	decreasing[2]	11	180524	increasing[3]	391	68287	decreasing[2]	4394
235986	decreasing[2]	29	23295	decreasing[2]	313	215217	decreasing[2]	1466
118253	decreasing[2]	24	207649	decreasing[2]	50	175427	decreasing[2]	97
149066	decreasing[2]	22	179699	decreasing[2]	63	139581	decreasing[2]	101
57877	decreasing[2]	17	80969	increasing[3]	1581	213001	decreasing[2]	209
210784	stable[1]	20	231714	decreasing[2]	61	19407	decreasing[2]	154
28868	increasing[3]	2834	26758	decreasing[2]	47	206372	increasing[3]	3146
240650	decreasing[2]	57	209761	decreasing[2]	69	2211	increasing[3]	2498
32073	increasing[3]	185	162567	increasing[3]	801	223491	increasing[3]	1232
117698	increasing[3]	28	141881	decreasing[2]	56	179840	decreasing[2]	61
29244	decreasing[2]	29	209530	decreasing[2]	26	105940	decreasing[2]	303
137778	increasing[3]	158	181266	increasing[3]	195	141479	decreasing[2]	976
175441	increasing[3]	48	197815	increasing[3]	312	138070	decreasing[2]	409
74395	increasing[3]	5464	18795	decreasing[2]	655	208508	decreasing[2]	286
85881	increasing[3]	186	18570	decreasing[2]	97	112002	decreasing[2]	3431
110358	decreasing[2]	26	85483	decreasing[2]	533	239926	decreasing[2]	99
139963	decreasing[2]	40	52134	decreasing[2]	35	141544	decreasing[2]	285
210158	increasing[3]	39	27423	decreasing[2]	486	210426	decreasing[2]	1111
57349	decreasing[2]	346	168664	decreasing[2]	70	237073	decreasing[2]	598
172635	increasing[3]	68	155851	decreasing[2]	160	240107	decreasing[2]	201
196652	increasing[3]	5582	83940	decreasing[2]	2087	25213	decreasing[2]	684
171960	decreasing[2]	41	201088	decreasing[2]	597	183514	decreasing[2]	161
200002	decreasing[2]	27	50850	decreasing[2]	45	147349	decreasing[2]	269
145920	increasing[3]	1730	1290	decreasing[2]	2316	3756	increasing[3]	35550
65112	decreasing[2]	26	70498	decreasing[2]	633			

[1] Ranking is steady.
[2] Ranking rises as users are more demanding of restaurant service, food, and environment.
[3] Ranking falls as users are more demanding of restaurant service, food, and environment.

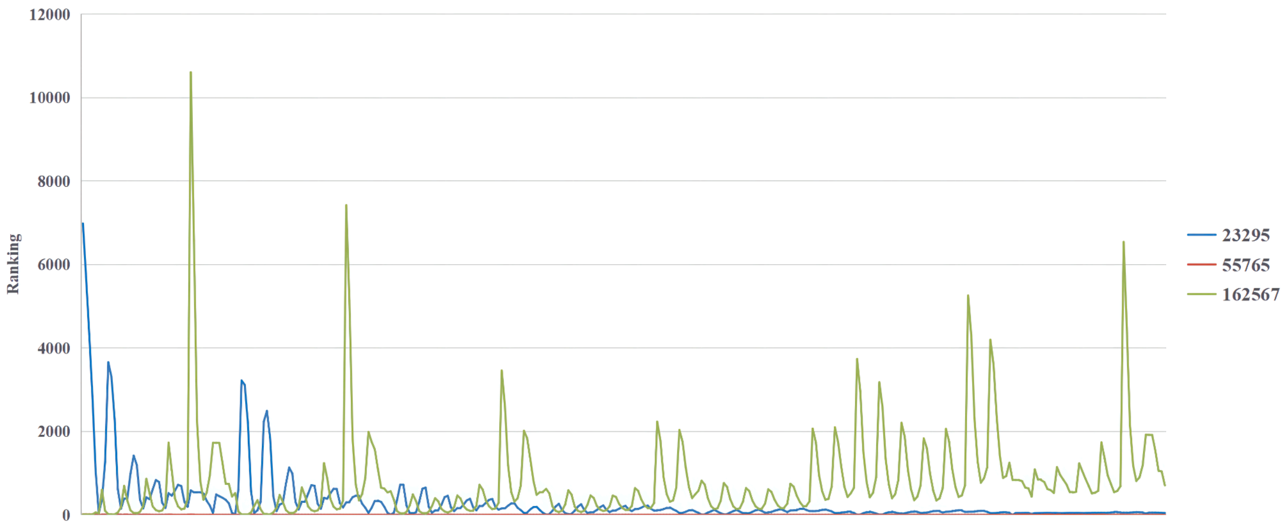

Fig. 9. Examples of changes in restaurant rankings. The closer to the X-axis, the higher the ranking. The level of user demand increases from left to right on the X-axis.

restaurants in Table 12 under 342 different scenarios (user demand for each restaurant criterion from lowest to highest). The average ranking of these 92 restaurants is also included in Table 13.

Considering Tables 12 and 13, it can be concluded that restaurants with a frequency of appearance in the top 10 for all 342 scenarios equal to or greater than 40% (even close to 40%) are those whose ranking is constant or increases as the user is more demanding of restaurant service, food, and environment. For restaurants with a frequency of appearance in the top 10 for the 342 scenarios less than 40%, some rank lower when the level of user demand is higher, and others rank higher when the level of user demand is higher.

In general, the changes in the ranking of these 92 restaurants can be divided into three different situations. Fig. 9 compares the differences between these three situations using the change in the ranking of several restaurants.

- Restaurants with stable ranking, although the levels of user demand of restaurant service, food, and environment change. For example, according to Table 13 and Fig. 9, the ranking of restaurant 55765 is stable and high, fluctuating among the top 10.
- Restaurants whose ranking increases as users are more demanding of restaurant service, food, and environment. For example, as shown in Fig. 9, restaurant 23295 ranks low when the levels of user demand of restaurant service, food, and environment are not very high. However, it achieves a higher ranking when users are more demanding. This indicates that this restaurant did not receive many extremely positive reviews, but hardly any negative ones. Thus, the ranking of this restaurant rises as users become pickier about restaurant service, food, and environment.
- Restaurants whose ranking falls as users are more demanding of restaurant service, food, and environment. For example, as shown in Fig. 9, restaurant 162567 ranks high when the levels of user demand of restaurant service, food, and environment are not very high. However, it achieves a lower ranking when users are more demanding. This means that although this restaurant received many very positive reviews, the negative ones are so bad that it drops in ranking as users become more critical and read more unfavorable reviews.

In fact, the preferences of users when reading reviews are proportional to their levels of demand of restaurant service, food, and environment. When users are not demanding, they only care about the favorable evaluations of the restaurant before going to eat there, ignoring the negative ones. In this case, the composite score calculated for the restaurant will be relatively high. In contrast, fussy users are likely to pay more attention to adverse evaluations, which reduces their perception of the restaurant's overall rating.

Combined with the composite score of each restaurant in Table 11, it can be observed that although the ranking of restaurant 55765 consistently fluctuates in the top 2, its composite score is (VG,-0.0204) when users are very undemanding of restaurant service, food, and environment (i.e., $Scenario_5$), while its composite score is (G,+0.3332) when users are extremely demanding of these three criteria (i.e., $Scenario_1$). Its composite score goes from slightly worse than "*Very Good*" to better than "*Good.*" As a result, those restaurants

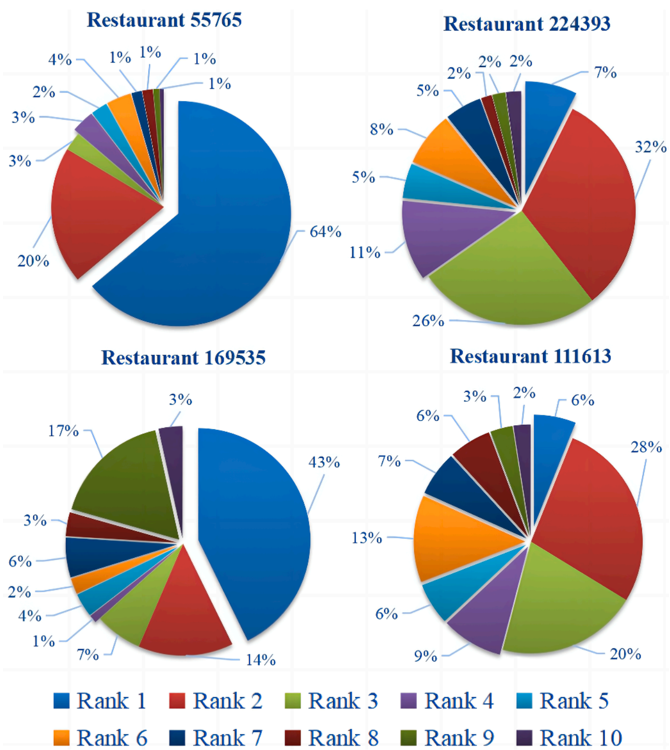

Fig. 10. Distribution of the ranking of restaurants with more than 70% frequency of appearance in the top 10 out of 342 scenarios.

whose ranking rises with increasing user demand (i.e., with more demanding users) may satisfy those who like to read negative reviews and have higher expectations for restaurant service, food, and environment. And those restaurants whose ranking goes down with increasing user demand may satisfy those who are undemanding or nearly not picky about any aspect of the restaurant.

Additionally, it can be concluded from Tables 12 and 13 that restaurants 55765, 224393, 169535, and 111613 not only appear frequently on the top 10 restaurants lists, but also maintain or improve their rankings when users are more demanding of restaurant service, food, and environment. Therefore, before users decide to make personalized restaurant rankings, these four restaurants can serve as comprehensive recommendations, as they can meet the needs of most users with different levels of demand.

However, comprehensive recommendations are also necessary to analyze how often they appear in the first place, second place, and so on. In that way, the platform can determine the ranking of each restaurant in the comprehensive recommendation. Fig. 10 shows the percentage of each ranking for the restaurants 55765, 224393, 169535, and 111613 over the total number of times they appeared in the top 10.

As shown in Fig. 10, restaurant 55765 not only appears most frequently in 342 scenarios, but also has the highest probability of being ranked first (i.e., 64% $\times$ 335 $=$ 214). Therefore, this restaurant should be ranked first among these four restaurants. Similarly, the frequency with which restaurant 224393 ranks second (i.e., 32% $\times$ 325 $=$ 104) is higher than that of the other restaurants. Therefore, it should be ranked second. By analogy, restaurants 111613 and 169535 should be ranked third and fourth, respectively.

6. Discussion

This paper introduces a novel decision support model that takes into account user demand levels for different restaurant aspects, the applicability of which has been demonstrated through user reviews of 78,512 restaurants on Dianping.com. This model uses various linguistic quantifiers to generate new variables that can reflect the levels of user demand for restaurant service, food, and environment. Each linguistic quantifier is mapped to a more easily understood business concept: the level of user demand. The proposed model also incorporates the degree of importance and linguistic quantifiers representing user demand levels. This allows for more accurate personalized weights to compute the restaurant's overall score. All these features improve the adaptability and comprehensibility of the proposed model in practical situations.

In addition, the proposed model can produce multiple scenarios of restaurant rankings to help users quickly select a restaurant that meets their levels of demand for the different restaurant aspects. This model not only includes the ranking generated by the arithmetic mean, but also generates more personalized rankings that consider the different user demand levels related to restaurant service, food, and environment. As shown in Section 5, when users have a medium level of demand for restaurant service, food, and environment (i.e., restaurant ratings are aggregated using the quantifier Q_4), the proposed model produces a restaurant ranking almost identical to that obtained using the arithmetic mean, while in other cases it is different.

Compared to the conventional approach of determining restaurant ranking using the arithmetic mean, the proposed model can also investigate the changing pattern of restaurant rankings with variations in user demand levels. Restaurants whose ranking rises as users become more demanding may satisfy those who like to read bad reviews and have higher expectations for restaurant service, food, and environment. Restaurants whose ranking decreases as users become more demanding may satisfy those who are nearly not picky about any of the restaurant criteria, as they tend to select it only based on positive reviews.

Moreover, except for the extreme case of randomly generating restaurant rankings to recommend to users, a more reasonable and comprehensive ranking of restaurants can be established from the 342 personalized ranking scenarios generated by the proposed model. Specifically, those restaurants with a frequency of appearance in the top 10 or top 20 above 70% (review platforms determine the number of restaurants recommended in the top positions) can meet the requirements of most users regardless of their levels of demand for restaurant service, food, and environment.

In summary, the main theoretical and practical contributions of the proposed model can be summarized as follows:

- From a theoretical point of view, the proposed model incorporates the linguistic quantifier to generate new criteria reflecting the different levels of user demand for restaurant service, food, and environment. Furthermore, linguistic quantifiers representing different levels of user demand have been associated with the degree of importance in calculating the weights of the corresponding criteria. This enables the acquisition of more accurate linguistic weights to compute the composite score for each restaurant, resulting in more precise restaurant rankings for users.
- From a practical point of view, the proposed model generates a more linguistically understandable composite score for each restaurant, taking into account the levels of user demand for restaurant service, food, and environment. Restaurant rankings, generated based on users' actual needs rather than simply average ratings, are presented through an interactive application, helping users quickly find a suitable restaurant. In addition, based on the frequency of the restaurant's appearance in the top 10 across various scenarios and its corresponding ranking, review sites can generate a list of restaurants that can satisfy the demands of most users with different levels of demand. This can increase customer satisfaction and foster trust in the decision-making process.

7. Conclusions and future work

The eWOM significantly influences customers' decision-making processes. Review sites, important sources of eWOM for customers seeking information, host a plethora of online reviews and ratings covering various hotels, restaurants, and entertainment venues. To make informed decisions when choosing a restaurant, many people read online reviews, which provide them with a wealth of information and give them more autonomy in their restaurant selection process. This paper introduces a new decision support model designed to help users quickly and accurately rank and select restaurants on Dianping.com based on their level of demand for various restaurant criteria. This approach uses the linguistic quantifiers of the 2LOWA aggregation operator to aggregate user ratings for each restaurant criterion. The IW method is proposed in this paper to obtain more accurate personalized weights based on user demand levels regarding restaurant service, food, and environment. Using more than 3.7 million restaurant reviews from Dianping.com, the feasibility and usefulness of the proposed model are demonstrated.

The personalized ranking of restaurants is displayed through an interactive application, demonstrating the effectiveness and interpretability of the proposed model in providing users with customized information. With this model, restaurants can be ranked according to different levels of user demand for restaurant service, food, and environment, rather than using the arithmetic mean that merely represents the average level of user demand. Moreover, according to the results of the Cox-Stuart test, restaurants that experience a rise in ranking with increasing user demand tend to satisfy those users who are more demanding and like to read negative reviews. Restaurants whose ranking decreases as users become more demanding may satisfy those users who are undemanding or hardly picky about any of the restaurant criteria. In this way, this model helps users more quickly choose a restaurant that aligns with their preferences.

The main contributions of the proposed model have been discussed in Section 6. However, this model also has the following limitations that need to be addressed:

- Although this paper has already taken into account the three most commonly accepted criteria that affect restaurant ranking—food, service quality, and restaurant environment—in reality, user decision-making in restaurant selection is dynamic, considering more criteria such as price, location, among others.
- The timeliness of online reviews has not been taken into account. However, older reviews, whether positive or negative, usually have less impact on the user’s decision-making.
- Since the proposed model requires conversion between numbers and scales for numerical computations (e.g., IW weights of each restaurant criterion in the computation of the overall score, ranking of restaurants, etc.), only ordinal variables on linguistic scales can be applied to this model. Qualitative variables such as the type of restaurant or restaurant location cannot be directly included in this model, as they lack numerical values that can be ordered in linguistic terms.
- The proposed model cannot process textual comments that capture nuanced details and personal experiences, even though they also play a significant role in influencing the restaurant selection process.

The above limitations should be addressed in future work. First, in order to take into account other criteria such as price, location, the popularity of the restaurant, etc., in the composite score and ranking, new data could be collected from other review sites such as TripAdvisor, OpenTable, or Yelp. Secondly, when calculating the composite score for each restaurant, the time frame for collecting online reviews could be limited to, for example, the most recent year or six months. This would improve the timeliness of restaurant reviews, providing users with more realistic restaurant rankings and recommendations. Thirdly, the proposed model could be improved by integrating it with other machine learning algorithms to address issues where certain qualitative variables cannot be ordered in linguistic terms. Fourth, future work should incorporate text mining techniques with the proposed model to deal with textual comments, providing a comprehensive analysis and better assisting users in making informed decisions when choosing a restaurant. Future research could also explore the application of the proposed model in restaurant classification to determine whether it can explain segmentation results with greater linguistic interpretability. Finally, the proposed model could be adapted to other domains, such as hotels, products and movies, testing its versatility and applicability.

Data availability

Dataset related to this article can be found at https://www.yongfeng.me/dataset/ (Zhang, 2013).

CRediT authorship contribution statement

Ziwei Shu: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Ramón Alberto Carrasco:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Funding acquisition. **Manuel Sánchez-Montañés:** Data curation, Writing – review & editing, Supervision, Funding acquisition. **Javier Portela García-Miguel:** Software, Project administration, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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