Multimedia Tools and Applications
https://doi.org/10.1007/s11042-022-13315-y

Personalized ranking of products using aspect-based sentiment analysis and Plithogenic sets

Devendra Kumar Tayal[1] · Sumit Kumar Yadav[2] · Divya Arora[1]

Received: 11 August 2021 / Revised: 14 December 2021 / Accepted: 30 May 2022

Abstract

The availability of the content on the web has increased enormously in the last decade. Many reviews are written by the users on the e-commerce websites for the products they buy. These reviews are read by customers who are interested in buying those products. Sometimes, these reviews are in thousands which makes it difficult to read them. Customers also want to search reviews based on their preferred aspects to make a buying decision. In this paper, a novel approach for Multi-Criteria Decision Making (MCDM) for multi-aspect based personalized ranking of the products is proposed. It characteristically uses customer preferences as one of the inputs for decision-making. Opinions on various aspects are extracted using Aspect-Based Sentiment Analysis (ABSA) which becomes the second input to the framework which uses Plithogenic sets. This model uniquely incorporating varying customer preferences by mapping them to plithogenic degree of contradictions and modelling linguistic uncertainties in online reviews to create a personalized ranking of products using plithogenic aggregation. It has been shown empirically that our approach outperforms the existing MCDM approaches namely TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and WSM (Weighted Sum Model) and some of the state-of-the-art methods.

Keywords Aspect-based sentiment analysis · MCDM · Plithogenic sets · Product ranking

1 Introduction

With the advancement of the web and e-commerce, the amount of content generated by the users online has increased multi-fold in the last decade. This content is also referred to as user-generated content or UGC [29]. UGC can be in the form of photos, videos, text, etc. Users post a lot of content on social media websites like Facebook, Twitter. With the help of Natural

✉ Divya Arora
divya.nasa.jul@gmail.com

1 Indira Gandhi Delhi Technical University for Women, Delhi, India

2 Income Tax Department, Delhi, India

Language Processing (NLP) techniques, this data has been used in the past to predict outcomes in sports encounters [43], e-learning [38], movie reviews [37], transportation [5], spam analysis [10], stock trends [22], etc. With the improvements in artificial intelligence and deep learning techniques for image processing [14, 52, 53], the opinions and sentiments in multimedia content can be mined to make better product recommendations. Apart from this, with the advent of e-commerce platforms, users post a lot of content in the form of product reviews, hotel reviews, movie reviews, etc. These reviews can be used to extract meaningful opinions and these opinions can further be used for better product sales [24], hotels recommendation [6], etc. NLP is a branch of computer science which deals with extracting the meaning of a sentence, finding sentiment, classifying text, performing social media analysis, topic modelling and predictive analysis, etc. Sentiment Analysis is a part of NLP which deals with subjectivity analysis and sentiment classification. Subjectivity analysis is classifying a sentence or part of a sentence as either subjective or objective. An objective word or a sentence has information that is factual in nature, and thus is low in opinion and views, whereas a subjective sentence contains the user's opinion and views thus has a sentiment value. These opinions and views have been mined to extract sentiments being echoed by the user [17, 32].

While buying a product, a customer generally wants to know about how the product ranks on various aspects. Different customers are interested in different aspects of a product. A customer looking for a gaming phone is interested in the RAM and graphics of the phone, while for another customer looks, camera or some other aspect might be the only important attribute. This brings forward a unique problem in making a buying decision. Customers need to find reviews on aspects of a product in which they are interested. Online reviews, given by other users are in hundreds or sometimes even in thousands and hence it becomes burdensome to read through them and find the reviews on aspects they are interested in. A customer might be interested in more than one aspect of the product e.g. while selecting a hotel, a customer might be interested in the location, sleep quality, and service considered together. This brings forward another problem in decision making, a user needs a solution that gives a consolidated view of a product (hotel in our case) on the aspects which are selected by the user. Figure 1 illustrates these two problems faced by the customers for the hotel selection. As illustrated, customer 1 wants good service, value for money, and better sleep quality while selecting a hotel whereas customer 2 gives more emphasis on the location and cleanliness of the hotel. To select a hotel, customer needs to find user reviews for their preferred aspects and then decide on those multiple aspects.

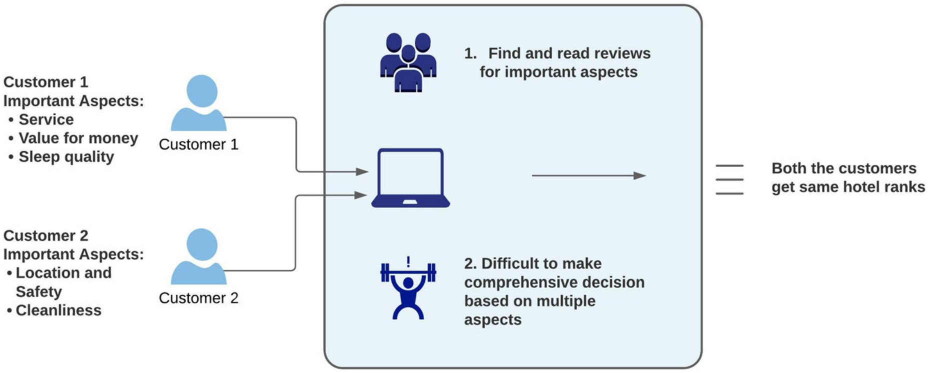

Fig. 1 Problems faced by the user for the hotel selection

Sentiment analysis has been widely used for product rankings, one of the popular approaches for sentiment-based product ranking relies on extracting features from reviews and matching those features with customer profiles to provide rankings [35]. Some other approaches rely on providing product recommendations based on reviews from like-minded users [19, 40]. While few others try to model customer preferences in terms of static weights, rather than considering changing preferences from one customer to another [54]. All these techniques either ignore or assume customers' preferences for various aspects of a product to make personalized recommendations. The linguistic uncertainty in textual reviews is not considered in all earlier works. The linguistic opinions expressed by the users in online reviews are characteristically uncertain and not crisp. While few works try to capture this uncertainty by proposing a distance-based utility function to convert linguistic terms like "good", "bad" etc. to numerical values [16]. But it has been shown in earlier works that plithogenic sets better capture textual subjectivity than many of the other techniques [34]. This paper proposes a novel method to solve the above deficiencies by incorporating varying customers' preferences and plithogenic based linguistic opinion modelling to provide rankings.

The main contributions of our paper are:

1. We propose a plithogenic sets-based MCDM method that models changing customer preferences. The proposed system is capable of giving varying recommendations, as per customers' provided aspect preferences.
2. The proposed method models linguistic opinion in a better way while solving MCDM problems using ABSA. The linguistic opinion is converted to aggregate sentiment ratings, which are mapped to the degree of appurtenance for the multi-attribute plithogenic set.

To best of our knowledge, this paper is first to incorporate both varying customers' preferences and capturing linguistic uncertainty. The proposed model accepts the customers' liking for aspects and user reviews to give a personalized hotel ranking to each user. ABSA is used to find aspects from textual reviews of the hotel, further, we find sentiments expressed on these aspects. Figure 2 illustrates the proposed solution to this problem. The model is validated by creating a hotel ranking system. A comparison of the proposed method is shown with other

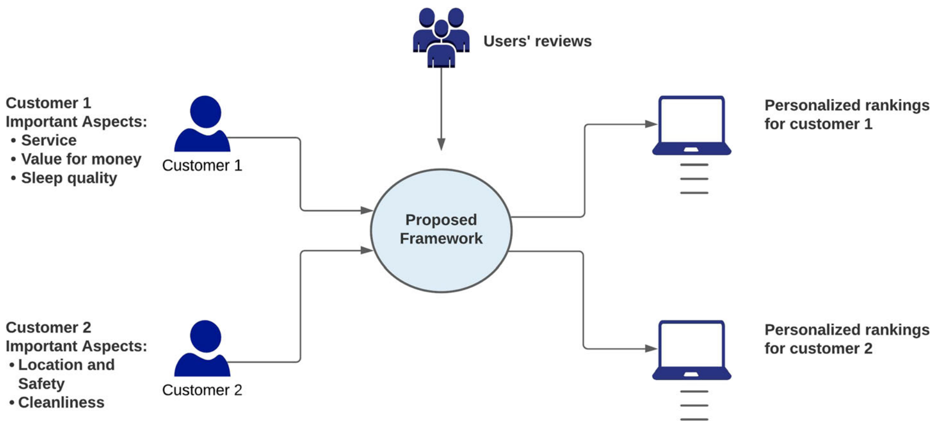

Fig. 2 Proposed solution for the problem

MCDM techniques and two similar ABSA-based outranking methods. It is proved empirically that our technique outperforms these techniques.

The rest of the paper is divided into the following sections: Section 2 describes briefly the related work. Section 3 provides an introduction to plithogenic sets. Section 4 gives a detailed description of the proposed methodology. Section 5 shows the set of experiments that were conducted based on the proposed methodology. Section 6 presents the comparison of proposed model with other techniques. Section 7 outlines the conclusion and future scope of this work.

2 Related work

2.1 Sentiment analysis

Sentiment analysis or finding sentiments of text has developed into a mature branch of computer science. Sentiment analysis can be done at the following levels: sentence level, document level, and aspect level [26]. Various studies have proven applications of sentiment analysis to different fields. Some authors studied how the sentiment of tweets on a game varied as the match results changed [45]. They showed a direct correlation between tweet sentiments and match states. Sentiment analysis of Facebook posts was done, and its results were used in e-learning content recommendations [33]. In some studies, authors did Aspect-Based Sentiment Analysis (ABSA) on mobile reviews to find aspects and what sentiments were expressed on these aspects to generate the opinionated summary of the reviews in a graphical form [12]. Some studies have shown how product recommendations can be done using ABSA, an integrated approach of using feature level sentiments of reviews on a product, to make a critiquing interface for recommender system is proposed [9]. Similarly, an application of sentiment analysis has been shown in the field of crime prediction [4].

ABSA has been widely studied in the literature for finding aspects and analyzing sentiments on these aspects. Some authors have used machine learning-based approaches (both supervised and unsupervised) to find aspects from the text. LDA was used to find reviews on specific aspects from the hotel and restaurant reviews provided by different users [44]. The other prominent way of ABSA is the syntactic technique. The authors used syntactic techniques to find aspects and showed how the grammatical structure of a sentence can be used to find aspects and achieved a precision of around 75% [51]. Haider et al. [13] studied what role is played by different forms of adverbs in the sentiment classification of tweets. They used syntactic techniques to extract adverbs and then obtained their sentiment scores through SentiWordNet to classify tweets into positive, negative, or neutral. The work uses syntactic techniques for Aspect extraction (AE) and feeds the knowledge extracted from the AE step to the ABSA step thus improving the accuracy [30]. Sentence syntactic knowledge was used to augment the CNN model to achieve higher accuracy [25]. Lexicon-based approaches were also used for sentiment classification and achieved results with improved accuracy [15, 31].

2.2 Sentiment analysis with MCDM

Many researchers have proposed aspect-based ranking models using Multi-criteria decision-making (MCDM) approaches. TOPSIS combined with AHP was used to make recommendations of smartphones based on features extracted using the Term Frequency (TF) approach [20], but the authors did not consider the relative importance of aspects for different customers.

Intuitionistic fuzzy set theory along with the Intuitionistic Fuzzy Weighted Averaging (IFWA) operator was used by authors to rank alternative products, but they did not emphasize the importance of weightage for different aspects [27]. Some authors calculated aspect weights using aspect frequency and attention degree, but this does not necessarily cater to all users, since different users have different preferences [50]. Page rank algorithm along with sentiment analysis was used for ranking of the products [48]. This was further improved by assigning weight to each review based on the date it was posted to calculate the age and number of votes given to that review [49]. The impact of undetermined weights was studied for ABSA [11]. They created a directed graph model for combining the sentiment score of textual reviews with the ratings of aspects. Page Rank method was also improved for obtaining the ranking of products by calculating the value of a node, which is the final score of a product. A comparison of alternative products can effectively be done using the directed graph which in turn can improve the ranking accuracy [21]. Some researchers have used intuitionistic fuzzy methods for ranking products using online data, the interval-valued intuitionistic fuzzy TOPSIS method was used for product ranking [28], they used intuitionistic fuzzy numbers to represent each product performance by considering their features. Also, the ranking of products of online textual reviews was obtained by aggregating the interval type 2 fuzzy numbers [8]. Ranking of aspects is done from the textual reviews which signify the important aspects of the product [46]. Reviewers' opinions are found using textual reviews from B2C websites, but preferences are not taken into consideration [23]. In all the above works the customer's aspect preferences are either not considered or a static aspect preference is considered to represent all the customers. In real-world scenarios, people have varied preferences for aspects and hence all the above works fail to model varying customer preferences. In recent times, some authors [16] proposed an approach that considers some order of varying customer preferences to feed into the ELECTRE MCDM model but the author falls short of creating a generic model which can be used for various types of preferences, further the author models linguistic subjectivity by creating a simplistic position based function. In [54], the author proposes ABSA based decision aid model which uses the number of times an aspect is being referred to as in reviews as customers' preferences, this is based on assumption that important aspects are the most talked about aspects in the online reviews. While this assumption is not completely wrong but still it fails to create a generic model, which can be used in all types of use cases.

In this paper, we use syntactic techniques augmented with domain knowledge for ABSA. We deal with linguistic uncertainty by modelling it using plithogenic sets. Further, we propose a novel approach to solve the problem of capturing varying users' preferences in MCDM. The detailed methodology is explained in section 4.

3 Introduction to Plithogenic sets

Plithogenic sets were introduced by Samarandache [41] and are defined as a generalization of crisp, fuzzy, intuitionistic fuzzy, and neutrosophic sets. The plithogenic sets are characterized by the degree of appurtenance or belongingness of an element of a set and the degree of contradiction between various values of an attribute with the dominant attribute. In the past, some studies have been done to show the usage of plithogenic sets for weight assignment in the existing MCDM techniques. Plithogenic aggregation operator is used in finding the aggregate value of subjective weights and weights obtained from the CRITIC method [1]. These weights were then used in TOPSIS to find the ranks of various alternatives in the field of supply chain management. Similarly, some other MCDM techniques with plithogenic sets were used to assign weightage for various available alternatives [2, 3].

3.1 Single attribute and multi-attribute plithogenic sets

In a single attribute plithogenic set, only one attribute or property is taken into consideration. For example, in a class of students, if only the height of students (single property) is considered then it will be a single attribute plithogenic set. It is defined as:

$$s(p, r, a, c) \tag{1}$$

Where,

s	a set or collection of items
p	a property (or attribute) of the elements in a set s
r	a range of values that p can take
a	the degree of appurtenance of an element x of a set, to set s
c	the degree of contradiction between various values of r

Similarly, if a plithogenic set is characterized by multiple attributes, then it is called a multi-attribute plithogenic set. In the previous example, if we also consider the weight of students along with height then it will be a multi-attribute plithogenic set.

Multi-attribute plithogenic sets can be defined as:

$$s\left(p_1, r_1, a_1, c_{1,}, p_2, r_2, a_2, c_2, \ldots\ldots\ldots, p_m, r_m, a_m, c_{m,}\right) \tag{2}$$

Where,

s	a set or collection of items
$p_1, p_{2,} \ldots.., p_m$	properties of a multi attribute plithogenic set
$r_1, r_{2,} \ldots.., r_m$	a range of values that $p_1, p_{2,} \ldots.., p_m$ can take
$a_1, a_{2,} \ldots.., a_m$	the degree of appurtenance
$c_1, c_{2,} \ldots.., c_m$	the degree of contradiction
m	number of attributes

3.2 Dominant attribute value

Out of all the values of an attribute represented by r, a value may be considered as a dominant value. This value is defined as a value that is most important in a range of values. It may however be noted that the dominant attribute value might not exist in all the scenarios or it may be difficult to define the dominant attribute value in many cases.

3.3 Degree of appurtenance

It is defined as a degree of belongingness or non- belongingness of an element x to a plithogenic set p.

The appurtenance takes the following values based on the set in consideration:

1. Crisp set: Complete membership (defined by 1), complete non-membership (defined by 0) [47]
2. Fuzzy set: Fuzzy membership of x to set S [0, 1] [47]
3. Intuitionistic Fuzzy set: Fuzzy membership and non-membership [7]
4. Neutrosophic set: Fuzzy membership, non-membership, and indeterminacy [39]

3.4 Degree of contradiction

The degree of contradiction is defined as a value by which various values of an attribute contradict each other. The degree of contradiction is defined by the following axioms:

$$c_{v_1 v_1} = 0 \tag{3}$$

$$c_{v_1 v_2} = c_{v_2 v_1} \tag{4}$$

Let us consider a set of people s, and property under consideration is the weight. If we assume that this property can take the following values:

$$w \equiv \{\text{fat}, \text{normal}, \text{thin}\} \tag{5}$$

Based on Eq. (3) and (4), the degree of contradiction between these values will be defined as:

$$c_{\text{fat},\text{fat}} = 0 \tag{6}$$

$$c_{\text{fat},\text{normal}} = 0.5 \tag{7}$$

$$c_{\text{fat},\text{thin}} = 1 \tag{8}$$

Value "fat" has zero contradiction with itself, whereas it is in complete contradiction with thin. Further the contradiction of fat with normal and normal with thin will be 0.5 indicating that these values have some contradiction amongst each other but are not pole apart.

3.5 Plithogenic aggregation operations

Plithogenic aggregation operators Plithogenic AND (intersection) & Plithogenic OR (union) are defined as a linear combination of fuzzy t_{norm} and fuzzy t_{conorm} [42].

$$\text{AND } [1 - c_{v_1 v_2}] \times t_{norm}(a_1, a_2) + c_{v_1 v_2} \times t_{conorm}(a_1, a_2) \tag{9}$$

$$\text{OR } [1 - c_{v_1 v_2}] \times t_{conorm}(a_1, a_2) + c_{v_1 v_2} \times t_{norm}(a_1, a_2) \tag{10}$$

3.6 Multi-attribute plithogenic sets aggregation operations

The multi-attribute plithogenic sets are an extension of single attribute plithogenic sets where the number of attributes in consideration is greater than one. For a multi-attribute plithogenic set with three attributes (a, b, c), the plithogenic intersection (AND) and plithogenic union (OR) is defined as:

$$x_1(a_k, b_l, c_m) \wedge x_2(a_k, b_l, c_m) = \begin{cases} \left[1 - c_{a_d,a_k}\right] \times t_{norm}(a_1, a_2) + c_{a_d,a_k} \times t_{conorm}(a_1, a_2), 1 \le k \le r_a \\ \left[1 - c_{b_d,b_l}\right] \times t_{norm}(b_1, b_2) + c_{b_d,b_l} \times t_{conorm}(b_1, b_2), 1 \le k \le r_b \\ \left[1 - c_{c_d c_m}\right] \times t_{norm}(c_1, c_2) + c_{c_d c_m} \times t_{conorm}(c_1, c_2), 1 \le m \le r_c \end{cases} \quad (11)$$

$$x_1(a_k, b_l, c_m) \vee x_2(a_k, b_l, c_m) = \begin{cases} \left[1 - c_{a_d,a_k}\right] \times t_{conorm}(a_1, a_2) + c_{a_d,a_k} \times t_{norm}(a_1, a_2), 1 \le k \le r_a \\ \left[1 - c_{b_d,b_l}\right] \times t_{conorm}(b_1, b_2) + c_{b_d,b_l} \times t_{norm}(b_1, b_2), 1 \le l \le r_b \\ \left[1 - c_{c_d c_m}\right] \times t_{conorm}(c_1, c_2) + c_{c_d c_m} \times t_{norm}(c_1, c_2), 1 \le m \le r_c \end{cases} \quad (12)$$

Where,

c_{a_d,a_k} is the degree of contradiction between the dominant value of a and other values for a
c_{b_d,b_l} is the degree of contradiction between the dominant value of b and other values for b
c_{c_d,c_m} is the degree of contradiction between the dominant value of c and other values for c
r_a is a range of values for a
r_b is a range of values for b
r_c is a range of values for c

4 Proposed methodology

Our proposed methodology can be divided into three units. First, Review Processing Unit (RPU), second, Customer Preference Processing Unit (CPPU), and third, Personalized Ranking Unit (PRU). In RPU, ABSA is done on textual reviews of hotels to extract aspects and their associated opinions. The CPPU processes customers' preferences. Both of these unit form input to the PRU. The PRU is the module for doing MCDM using customer preferences and hotels' sentiment ratings. Figure 3 shows the proposed framework. This section is further subdivided into the following sections: Section 4.1 provides the details of the dataset which is being used for the approach. Section 4.2 shows how reviews are processed in RPU. Section 4.3 explains how CPPU represents customer preferences to plithogenic sets. Finally, Section 4.4 describes the PRU giving a detailed demonstration of the proposed approach using two hotels from the dataset.

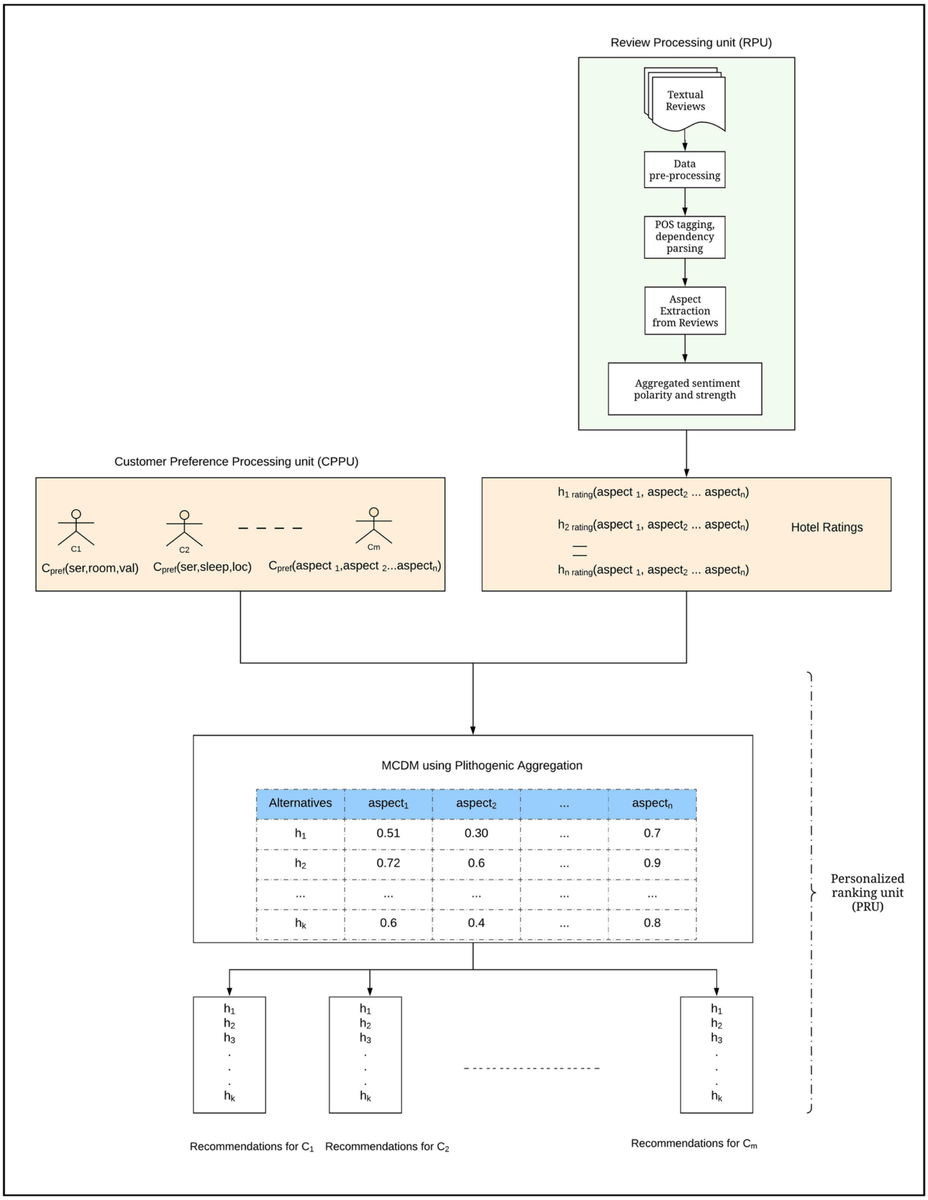

Fig. 3 Proposed Framework

4.1 Dataset

The dataset for demonstration of the proposed framework was obtained from TripAdvisor[1]. The dataset was in the form of JSON files, with one file for each hotel. This file has the following information about the hotel:

- Hotel's identification information, which consists of TripAdvisor hotel's Id, hotel's name, hotel's address, and hotel's website information

- Star ratings, the data consist of star rating on different aspects like location, value for money, sleep quality, etc. and an overall star rating is also available for the hotel. In this paper, we utilize these star ratings to create a baseline, to benchmark the performance of our ranking method
- Textual reviews are the reviews that users have posted on TripAdvisor for the hotel

We created a data crawler to extract all hotels in a given location. This was necessary since the comparison of hotels in the same location is generally required by the customers. Then star ratings and textual reviews are extracted for these hotels for data processing. For our experiments, we selected hotels in Seattle, the dataset consisted of 247 hotels in Seattle.

We selected a subset of these hotels based on TripAdvisor rankings for these hotels. Out of these 247 hotels present in the dataset, only 117 had rankings available on TripAdvisor. Further, we describe how we use these rankings to create a second baseline for performance evaluation. From these 117 hotels, we tried to include hotels with high, medium, and low rankings in our selection. Finally, we selected 20 hotels for comparisons and concept demonstrations. The selected hotels can be seen in Table 1, along with TripAdvisor ranks and the number of user reviews available on each hotel in the dataset.

4.2 Reviews processing unit (RPU)

This unit is used for extracting the sentiments from the textual reviews on hotels given by users. Data is cleaned by the removal of stop words followed by stemming and lemmatization. Data is POS tagged using Stanford Part-of-Speech Tagger and dependency parsing is done using Stanford dependency parser. Aspects are extracted from the reviews and domain knowledge-based aspect mapping is done to the aspect categories, e.g. the aspect category service is constituted of various aspects like manager behavior, room service, check-in process, welcome experience, etc. The aspect category “Location” covers words such as area, place,

Table 1 Selected list of hotels in Seattle

Hotel Id	Hotel Name	Hotel Location	Zip Code	TripAdvisor Ranks	Number of reviews
100504	Hotel Monaco Seattle	Seattle	98101	17	422
100505	Warwick Seattle Hotel	Seattle	98121	52	298
100506	Hotel Seattle	Seattle	98101	114	48
100507	Inn at the Market	Seattle	98101	1	527
100508	Kings Inn	Seattle	98121	106	52
100509	Ace Hotel	Seattle	98121	46	97
100527	Crowne Plaza Seattle Downtown Area	Seattle	98101	49	272
100537	Inn at Queen Anne	Seattle	98102	88	121
100538	Inn at Virginia Mason	Seattle	98104	81	30
100540	MarQueen Hotel	Seattle	98109	69	128
100542	Mayflower Park	Seattle	98101	13	409
100544	Moore Hotel	Seattle	98101	65	291
100547	Executive Hotel Pacific	Seattle	98104	70	307
100554	Renaissance Seattle Hotel	Seattle	98104	60	313
100560	Hilton Seattle	Seattle	98101	78	124
100561	Quality Inn & Suites Seattle	Seattle	98109	96	149
100562	Sheraton Seattle Hotel	Seattle	98101	16	700
100564	Sixth Avenue Inn	Seattle	98121	76	218
100565	Hotel Andra	Seattle	98121	9	365
100567	The Edgewater Hotel Seattle	Seattle	98121	53	522

location, distance, locality, venue, neighbourhood, address, vicinity, etc. A similar set was created for "Value for money" containing elements like price, value, dollar, charge, cost, rate, amount, fare, tariff, worth, etc. Similar mappings are created for other aspect categories namely "Room Quality" and "Sleep Quality". Further, opinion extraction is done to obtain opinion words. The opinion words are used to find sentiment polarity and strength using SentiWordNet. Aggregated normalized sentiment ratings are found on the above-mentioned aspect categories using all reviews given by reviewers on a particular hotel. These aggregated normalized ratings are mapped to the degree of appurtenance for the multi-attribute plithogenic set. This way we can convert linguistic uncertain opinions to numerical values for further evaluation in the model. For experiments, we created our model to work for three aspects namely service (denoted by ser), room quality (denoted by room), and value for money (denoted by val), but this model can be further extrapolated to any number of aspects. The aggregated hotel sentiments ratings based on three aspects can be defined as:

$$\mathrm{h_{rating}} = (\mathrm{ser}, \mathrm{room}, \mathrm{val}) \tag{13}$$

4.3 Customer preference processing unit (CPPU)

In this module, the customer preferences for aspects are taken as input. The preferences may vary from customer to customer. For illustration purposes, the customer preferences $\mathrm{c_{pref}}$ based on the three aspects as discussed in the above section can be defined as:

$$\mathrm{c_{pref}}(\mathrm{ser}, \mathrm{room}, \mathrm{val}) \tag{14}$$

For a customer desiring high preference of aspects service, room and low preference of aspect value for money, the $\mathrm{c_{pref}}$ will be defined as:

$$\mathrm{c_{pref}}(\mathrm{ser}, \mathrm{room}, \mathrm{value}) = \{\mathrm{high}, \mathrm{high}, \mathrm{low}\} \tag{15}$$

As stated in the previous sections, the degree of contradiction is defined as the contradiction of each element of a set with the dominant attribute of that set. To calculate the degree of contradiction, the range r for each aspect is defined by three values,

$$\mathrm{r} = \{\mathrm{high}, \mathrm{medium}, \mathrm{low}\} \tag{16}$$

The "high" is considered a dominant preference and is assigned the value of 1. The corresponding contradiction values can be calculated based on user preferences. For aspect "room" customer's preference is high (considered as 1), degree of contradiction with dominant preference as per Eq. (3) will be:

$$\mathrm{c}_{\mathrm{room_d room_{cust}}} = \mathrm{c}_{1,1} = 0 \tag{17}$$

Similarly, for "service"

$$\mathrm{c}_{\mathrm{service_d service_{cust}}} = \mathrm{c}_{1,1} = 0 \tag{18}$$

For "value of money", user preference is low (which indicates that the customer is not concerned with the cost), so the degree of contradiction will be:

$$\mathrm{c}_{\mathrm{value_d, value_{cust}}} = \mathrm{c}_{1,0} = 1 \tag{19}$$

The higher degree of contradiction with dominant preference indicates that this aspect does not hold high importance for the user. Whereas the lower degree of contradiction with dominant preference indicates higher importance of an aspect for the user.

4.4 Personalized ranking unit (PRU)

PRU accepts two inputs, first hotel's aggregated sentiment ratings obtained from RPU and the second customers' preferences obtained from CPPU. To find personalized multi aspect-based ranking, we have used multi-attribute plithogenic sets aggregation between customer's preferences and hotels aggregated sentiment ratings. The main advantage of this methodology is that it considers customers' preferences to create the preference matrix whereas the other methods like TOPSIS and WSM give no importance to customers' preferences for aspects. These methods just consider experts' opinions to create the preference matrix and hence give the same recommendations to all the customers irrespective of their preferences. Accordingly, Eq. (11) can be transformed as.

$$c_{pref}(ser, room, val) \wedge h_{rating}(ser, room, val)$$
$$= \begin{cases} \left[1 - c_{ser_d, ser_{hotel}}\right] \times t_{norm}(ser_{cust}, ser_{hotel}) + c_{ser_d, ser_{hotel}} \times t_{conorm}(ser_{cust}, ser_{hotel}) \\ \left[1 - c_{room_d, room_{hotel}}\right] \times t_{norm}(room_{cust}, room_{hotel}) + c_{room_d, room_{hotel}} \times t_{conorm}(room_{cust}, room_{hotel}) \\ \left. 1 - c_{val_d, val_{hotel}}\right] \times t_{norm}(val_{cust}, val_{hotel}) + c_{val_d, val_{hotel}} \times t_{conorm}(val_{cust}, val_{hotel}) \end{cases} \tag{20}$$

Where values for $t_{norm}$and t_{conorm} are calculated as:

$$t_{norm}(ser_{cust} ser_{hotel}) = ser_{cust} \wedge ser_{hotel} = ser_{cust} \times ser_{hotel} \tag{21}$$

$$t_{conorm}(ser_{cust}, ser_{hotel}) = ser_{cust} \vee ser_{hotel} = ser_{cust} + ser_{hotel} - ser_{cust} \times ser_{hotel} \tag{22}$$

For calculation purposes, the customer's preferences are assigned the following values, high preference is assigned value 1, medium preference is assigned value 0.5 and low preference is assigned value 0.1. The values obtained from the above equation are fed into the preference matrix for this hotel. Similarly, the customers' preferences are aggregated with other hotels' ratings to complete the preference matrix for all available alternatives. Further, to rank the alternatives we calculate the aggregate preference score of each alternative using the eq. (23).

$$p_i = \sqrt{\sum_{j=1}^{n} c_j^2} \tag{23}$$

Where p_i the preference score for i^{th} alternative and c_j is the j^{th} criterion.

To show our concept, we will be demonstrating it on data obtained from two hotels in Seattle i.e. Hotel Inn at the Market and Hotel Seattle. Table 2 shows aggregated sentiment scores obtained from section RPU for three aspects namely room, service, and value for money. All these three criteria are beneficial and therefore high values for these are desired. Using the customer's preferences from CPPU the preference matrix is created in PRU. Table 3 shows the preference matrix obtained for the two alternatives and three criteria.

Table 2 Aggregate sentiment scores

Hotel Name	Hotel Id	Room	Service	Value for money
Hotel Inn at the Market	100507	0.6073	0.6580	0.6472
Hotel Seattle	100506	0.4648	0.5948	0.5031

The aggregated preference scores for the above given two hotel alternatives are shown in the last column of Table 3. The results obtained show that the hotel "Hotel Inn at the Market" is better suited to the user's preferences as compared to the "Hotel Seattle".

5 Experiments and results

We conducted a series of experiments in Spyder IDE, using python 3.7 to show how our method changes hotel recommendations based on different customers' preferences. The simulation of our model was done for three customers with different aspect preferences which are shown in three cases.

Case 1 For customer 1 with preferences : $c_{pref}(ser, room, val) = \{high, high, low\}$

Here, the customer has selected three aspects namely service (denoted by ser), room quality (denoted by room), and value for money (denoted by val). His preferences for these aspects are high, high, and low respectively. Firstly, the aggregate sentiment scores were found through RPU. Then, the ranking of hotels is done using PRU. Table 4 shows the aggregate sentiment scores and aggregate preference scores obtained based on customers' preferences. The results are arranged in descending order of ranking recommendations for the customer with the highest-ranked hotel on the top.

Case 2 For customer 2 with preference : $c_{pref}(room, ser, loc) = \{medium, medium, high\}$

Here customer's preferences are medium, medium, and high for the aspects room, service, and location respectively. The aggregated sentiment scores and ranking of hotels are done using the same methods as mentioned in case 1. Table 5 shows the aggregate sentiment scores and the aggregate preference scores obtained based on customer 2 preferences. The results are arranged in descending order of aggregated preference scores, so hotels are suited to users' preferences in the same order.

Case 3 For Customer 3 with preference : $c_{pref}(room, ser, loc) = \{medium, high, high\}$

This customer is using the same aspects (room, service & location) as in case 2 but with different preferences. The similar method to cases 1 and 2 is adopted for finding the aggregate

Table 3 Preference matrix for two alternatives and three criteria

	Criteria/Aspects			Aggregated preference scores
Alternatives	Room	Service	Value for money	
100507	0.64	0.69	0.68	1.12
100506	0.46	0.59	0.55	0.94

Table 4 Ranking Results in descending order for customer 1 preferences c_{pref}(ser, room, val) = {high, high, low}

Hotel Id	Aggregate sentiment scores for aspects			Aggregate preference scores
	Room	Service	Value for money	
100538	0.6294	0.6677	0.6487	1.1444
100507	0.6073	0.6580	0.6472	1.1258
100561	0.5217	0.6321	0.7313	1.1165
100540	0.5686	0.6471	0.6744	1.1144
100542	0.5503	0.6505	0.6733	1.1065
100527	0.5996	0.6396	0.6237	1.0982
100564	0.5587	0.6445	0.6516	1.0949
100562	0.6099	0.6402	0.5830	1.0827
100565	0.5639	0.6412	0.6230	1.0797
100505	0.5649	0.6391	0.6145	1.0743
100554	0.5949	0.6573	0.5514	1.0684
100544	0.5612	0.6043	0.6393	1.0659
100504	0.5888	0.6386	0.5630	1.0596
100547	0.4960	0.6549	0.6049	1.0441
100567	0.5890	0.6554	0.5067	1.0420
100560	0.5325	0.6516	0.5654	1.0387
100537	0.5090	0.5871	0.6351	1.0271
100509	0.5542	0.6134	0.5236	1.0049
100506	0.4648	0.5948	0.5031	0.9356
100508	0.4692	0.4912	0.5875	0.9257

Table 5 Ranking results in descending order for customer 2 preferences c_{pref}(room, ser, loc) = {medium, medium, high}

Hotel Id	Aggregate sentiment scores for aspects			Aggregate preference score
	Room	Service	Location	
100565	0.5639	0.6412	0.7231	1.0637
100527	0.5996	0.6396	0.6870	1.0483
100504	0.5888	0.6386	0.6905	1.0475
100507	0.6073	0.6580	0.6702	1.0444
100542	0.5503	0.6505	0.6950	1.0439
100562	0.6099	0.6402	0.6677	1.0387
100567	0.5890	0.6554	0.6478	1.0247
100505	0.5649	0.6391	0.6581	1.0203
100564	0.5587	0.6445	0.6559	1.0188
100509	0.5542	0.6134	0.6707	1.0186
100547	0.4960	0.6549	0.6741	1.0178
100554	0.5949	0.6573	0.6326	1.0172
100544	0.5612	0.6043	0.6531	1.0064
100540	0.5686	0.6471	0.6301	1.0057
100538	0.6294	0.6677	0.5848	1.0009
100560	0.5325	0.6516	0.6189	0.9905
100561	0.5217	0.6321	0.6107	0.9769
100537	0.5090	0.5871	0.6154	0.9637
100506	0.4648	0.5948	0.5377	0.9064
100508	0.4692	0.4912	0.4697	0.8373

sentiment scores and hotel rankings. Table 6 shows the aggregate sentiment scores and aggregate preference scores obtained. The results are arranged in descending order of aggregated preference scores, so hotels are suited to users' preferences in the same order.

From case 2 to case 3, the preference of aspect service is changed from medium to high. The first hotel rank is the same in both cases. In case 2 the hotel with id 100,527 is rated higher than the hotel with id 100,507, whereas in case 3 hotel with id 100,507 is rated higher. This is so because, if the user's preference is near to the dominant criterion, our algorithm gives more preference to that attribute. In the first case, the location is near to the dominant value (contradiction is 0), so preference is given to this attribute. In the second case, service, and location both attributes are near to the dominant value (contradiction is 0 for both) so a combination of these two attributes is given more preference.

Also, it should be noted from the results that if a preference for an attribute is rated medium or low by the user, our algorithm does not recommend hotels that are rated low for these attributes, which we believe is the right thing to do. If a user gives preference as low or medium, it simply means that these attributes are of medium or low importance to the user and not that he wants to filter out hotels with the scores as medium or low for these attributes. A user would still desire to have filtering based on high scores for these criteria.

To better visualize our results, 3D graphs with a heat map were created which are shown in Figs. 4, 5 and 6 for all three cases respectively. In Fig. 4, the x, y, and z coordinates depict the aggregate sentiment ratings for the criteria room, service, and value for money. In Figs. 5 and 6, the coordinates depict the aggregate sentiment ratings for the criteria room, service, and location. Each point in all the figures represents a hotel. The hotels are colour mapped based on

Table 6 Ranking Results in descending order for customer 3 with preferences $c_{pref}(room, ser, loc) = \{medium, high, high\}$

Hotel Id	Aggregate sentiment scores for aspects			Aggregate preference score
	Room	Service	Location	
100565	0.5639	0.6412	0.7231	1.1031
100507	0.6073	0.6580	0.6702	1.0902
100527	0.5996	0.6396	0.6870	1.0878
100542	0.5503	0.6505	0.6950	1.0872
100504	0.5888	0.6386	0.6905	1.0868
100562	0.6099	0.6402	0.6677	1.0788
100567	0.5890	0.6554	0.6478	1.0704
100554	0.5949	0.6573	0.6326	1.0640
100547	0.4960	0.6549	0.6741	1.0636
100564	0.5587	0.6445	0.6559	1.0611
100505	0.5649	0.6391	0.6581	1.0607
100538	0.6294	0.6677	0.5848	1.0520
100509	0.5542	0.6134	0.6707	1.0507
100540	0.5686	0.6471	0.6301	1.0494
100560	0.5325	0.6516	0.6189	1.0364
100544	0.5612	0.6043	0.6531	1.0360
100561	0.5217	0.6321	0.6107	1.0166
100537	0.5090	0.5871	0.6154	0.9889
100506	0.4648	0.5948	0.5377	0.9358
100508	0.4692	0.4912	0.4697	0.8348

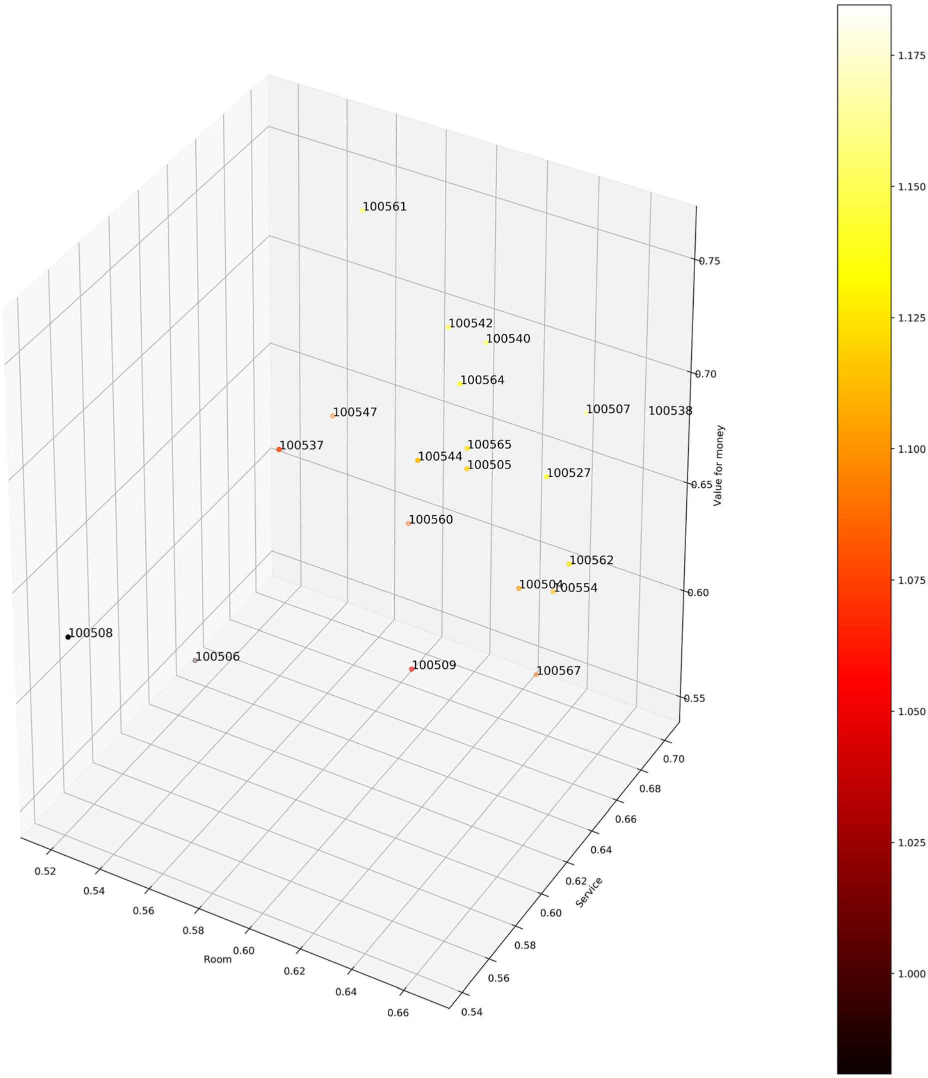

Fig. 4 3D plot with a heat map for hotel ranking based on customer 1 preference

the preference scores obtained from our approach. The hotels with lighter colours depict high scores (high ranking) and hotels with dark shades depict low scores (low rankings).

6 Performance evaluation and comparison

Performance evaluation of the proposed framework is done by comparing it with two existing MCDM techniques, TOPSIS and WSM, and two latest state-of-the-art methods. Two well-established standard bivariate rank correlation comparison statistical methods, namely the

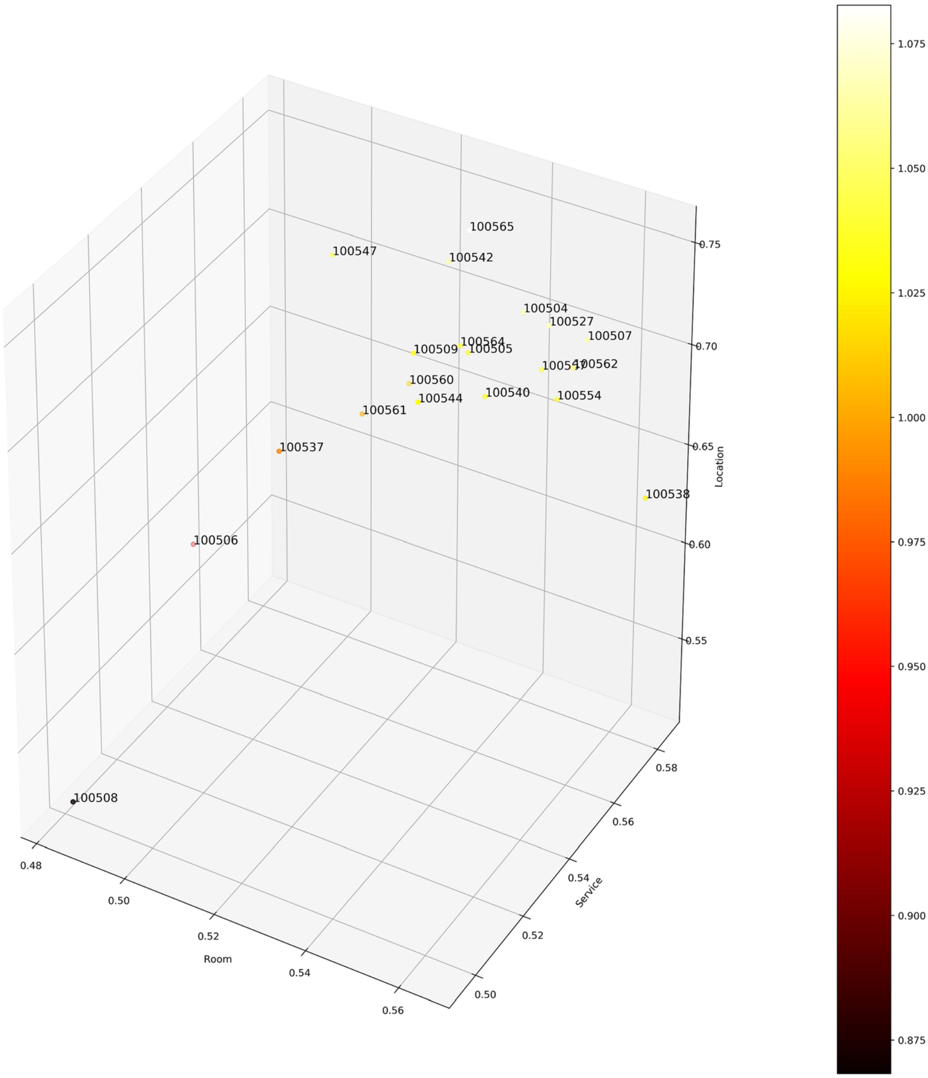

Fig. 5 3D plot with a heat map for hotel ranking based on customer 2 preference

Kendall's tau rank correlation method, and the Pearson's r correlation method were used to compare the efficacy of our model with respect to the above-said methods.

6.1 Performance evaluation measures

Kendall's tau Rank Correlation method is used to find ordinal relation between two monotonic measured quantities [18]. Kendall's coefficient τ is a measure of the correlation between two quantities. Kendall's tau coefficient ranges between 0 and 1, with 0 denoting no correlation and 1 denoting complete correlation. Mathematically, Kendell coefficient τ is defined as:

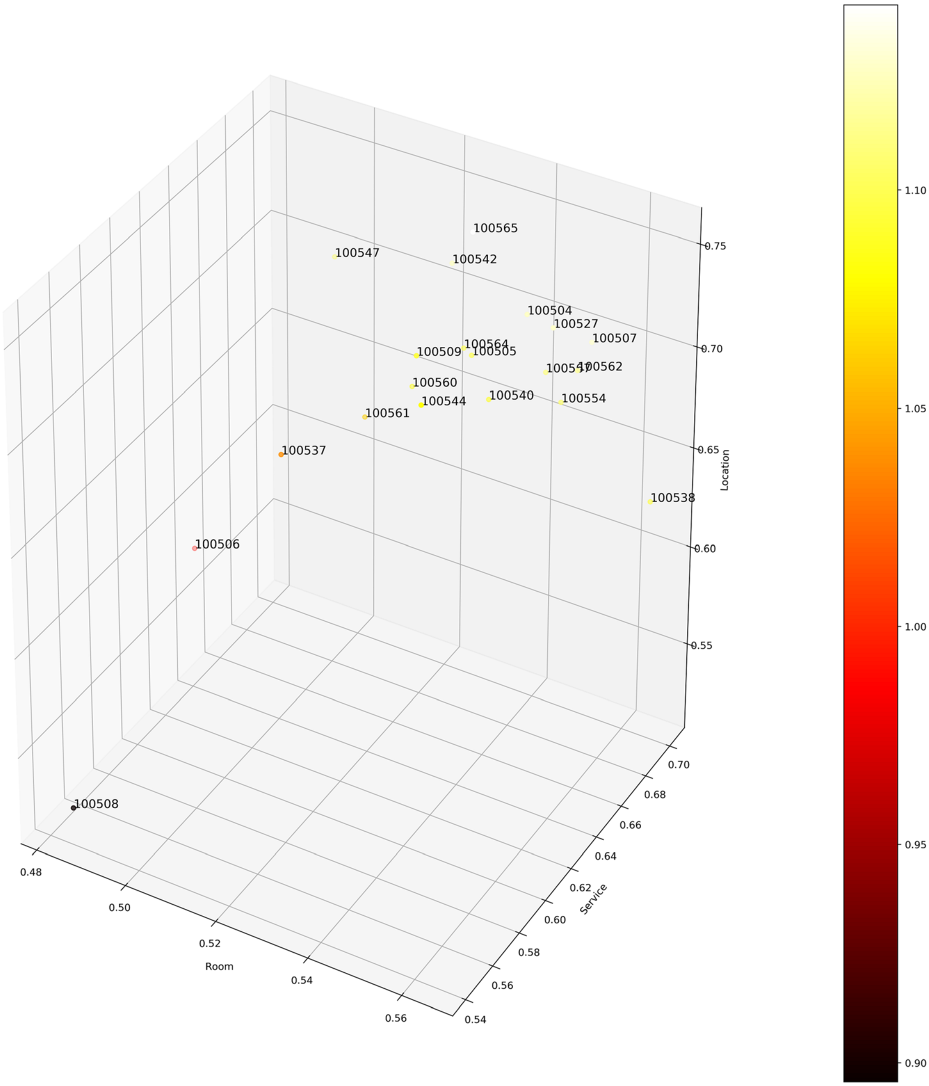

Fig. 6 3D plot with a heat map for hotel ranking based on customer 3 preference

$$\tau = \frac{n_c - n_d}{n(n-1)/2} \tag{24}$$

Where,

n_c stands for the number of concordant pairs
n_d stands for the number of discordant pairs

Pearson's correlation coefficient ρ is used to find the bivariate correlation between two variables [36]. It is defined as the covariance between two variables divided by the standard deviation. The value of this Pearson's correlation coefficient ranges between −1 and 1. 1 indicates a complete positive correlation whereas −1 indicates a complete negative correlation. 0 indicates no correlation between the datasets.

Mathematically, Pearson's r coefficient ρ is defined as:

$$\rho(a, b) = \frac{cov(a,\ b)}{\sigma_a \sigma_b} \tag{25}$$

Where,

cov(a, b)	is the covariance between a and b,
σ_a	is the standard deviation of a
σ_b	is the standard deviation of b

6.2 Comparison with existing MCDM techniques

To compare the results of our technique we have used two baseline rankings. First, based on the hotels ranks on TripAdvisor. All hotels in a location listed on TripAdvisor have an associated rank based on users' reviews. The ranks for hotels selected by us can be seen in Table 1. Relative TripAdvisor ranks are obtained for the hotels. These ranks were used to create the first baseline for comparison. The second baseline for comparison was created using the star rating given by the users. As described in section 4.1, our datasets consist of star ratings given by users on various aspects. Ranks based on aggregated normalized star ratings for the aspects selected by the customer were used to create a second baseline for result validation and performance analysis. The last two columns of Table 7 show the two baseline rankings for these hotels.

The MCDM techniques TOPSIS and WSM are simulated on the same dataset for comparison with the proposed methodology. Out of the two selected techniques for comparison, the first approach, TOPSIS is a distance-based approach, and the second, WSM is a weight-based approach. Table 7 shows the comparison results between the proposed methodology and these two techniques. These results are shown for customer preferences, $c_{pref}(room,\ ser,\ loc) = \{medium,\ medium,\ high\}$. Here, column 2 shows the ranks obtained for this user from our approach. The corresponding preference scores can be referred from Table 5. Columns 3 and 4 show the TOPSIS performance scores and rankings. Columns 5 and 6 show the WSM preference scores and the hotel rankings.

Using these two correlation methods we find ranking correlation coefficient between ranking obtained from our approach with the two baselines described above. Further, to compare our results with other MCDM techniques we find rankings using TOPSIS and WSM and compare them with baselines.

The statistical methods (Kendall's Tau and Pearson's r) are applied to the proposed approach, TOPSIS, and WSM by considering the two baselines. Table 8 shows the correlation results obtained between the techniques and TripAdvisor baseline ranks (first baseline). It can be seen that the proposed method has achieved a 76.84% correlation under Kendall's tau and a 91.58% correlation under Pearson's r. TOPSIS and WSM have achieved 75.79% and 69.47% correlation under Kendall's tau respectively, 69.47% and 85.86% correlation under Pearson's r. Table 9 shows the correlation results obtained between the techniques and ranks based on the star rating (second baseline). It is seen that the proposed method has achieved a 61.05% correlation under

Table 7 Result comparison of the proposed technique with TOPSIS and WSM

Hotel id	Proposed method ranking	TOPSIS Performance scores ($\mathbf{p_i}$)	TOPSIS rankings	WSM Preference scores$\left(\mathbf{a_i^{wsm}}\right)$	WSM rankings	Relative TripAdvisor ranks	Star ratings-based ranks
100565	1	0.8463	2	1.3256	1	2	4
100527	2	0.8490	1	1.3066	2	7	9
100504	3	0.8433	3	1.3043	3	5	3
100507	4	0.8135	4	1.3028	4	1	1
100542	5	0.7287	8	1.2955	5	3	2
100562	6	0.8014	5	1.2576	10	4	6
100567	7	0.7145	10	1.2701	7	9	10
100505	8	0.7262	9	1.2602	8	8	12
100564	9	0.7927	6	1.2928	6	14	13
100509	10	0.7312	7	1.2545	11	6	7
100547	11	0.6706	13	1.2496	12	13	17
100554	12	0.6885	12	1.2588	9	10	14
100544	13	0.6899	11	1.2358	14	11	11
100540	14	0.6534	14	1.2380	13	12	5
100538	15	0.5797	16	1.2334	15	16	8
100560	16	0.5854	15	1.2110	16	15	15
100561	17	0.5430	17	1.1877	17	18	18
100537	18	0.5199	18	1.1635	18	17	16
100506	19	0.2796	19	1.0676	19	20	19
100508	20	0.0110	20	0.9500	20	19	20

Kendall's tau and a 76.99% correlation under Pearson's r. TOPSIS and WSM have achieved 57.89% and 55.79% correlation under Kendall's tau respectively. Also, both these techniques have achieved 74.29% and 72.93% correlation under Pearson's r. Figures 7 and 8 show viz. a viz. comparison for the proposed method, TOPSIS, WSM with the two baselines. This shows that our proposed approach outperforms both TOPSIS and WSM. We were able to achieve a ranking that was more strongly related to both the baselines as compared to the existing techniques. TOPSIS and WSM are designed to work on the basis of experts' views and do not take any inputs for customers' preferences. The improvement in results can be attributed to our model's unique design, which inherently incorporates customers' preferences while making recommendations.

6.3 Comparison with state-of-the-art methods

We compared the proposed model with two latest state-of-the-art methods namely Sentiment Analysis based Multi-person Multi-criteria Decision Making (SA-MpMcDM) methodology [54] and SentiRank [16]. In the former method, the authors proposed a model to rank alternatives using users' reviews and numerical ratings. Static customer preferences were considered by assigning weights to aspects based on the number of times they were referred in the reviews. In SentiRank method, authors presented an approach to combine user

Table 8 Bivariate correlation results with TripAdvisor ranking

Technique	Kendall tau	Pearson's r
Proposed method	0.7684	0.9158
TOPSIS	0.7579	0.8857
WSM	0.6947	0.8586

Table 9 Bivariate correlation results with ranking based on star ratings

Technique	Kendall tau	Pearson's r
Proposed method	0.6105	0.7699
TOPSIS	0.5789	0.7429
WSM	0.5579	0.7293

preferences with other customers reviews and use ELECTRE-III to rank alternatives. In both these works, the dataset was obtained from TripAdvisor restaurant reviews. In SA-MpMcDM the ranking of 4 restaurants in the city of London was done whereas in SentiRank the authors used 22 restaurants from the city of Tarragona in Spain. We used the same dataset to compare the performance of our methodology with the above-said techniques.

6.3.1 Comparison with SA-MpMcDM

In SA-MpMcDM, authors used six restaurants aspects: Food, Service, Drinks, Ambience, Location, and Restaurant. The sentiment ratings on the first five aspects were extracted from textual reviews whereas the ratings on the Restaurant aspect were taken from the overall numerical rating of the restaurant. They assigned following weights to these aspects w_{food} = 0.387, $w_{service}$ = 0.125, w_{drinks} = 0.03, $w_{ambience}$ = 0.111 $w_{location}$ = 0.041 and $w_{restaurant}$ = 0.306. For comparison with our model: 1) We merged the food and drinks aspects as they are similar, accordingly we simulated our proposed method with five aspects: Food, Service, Ambience, Location, and Restaurant. 2) In our model we do not consider numerical ratings for the Restaurant aspect, so instead we used overall aggregated sentiments ratings of textual reviews for the restaurant. 3) Further, the above-mentioned weights were mapped to the following user preferences based on relative weights assigned to them by authors in their work:

$$c_{pref}(\text{Food}, \text{Service}, \text{Ambience}, \text{Location}, \text{Restaurant}) = \{\text{high}, \text{medium}, \text{medium}, \text{low}, \text{high}\}$$

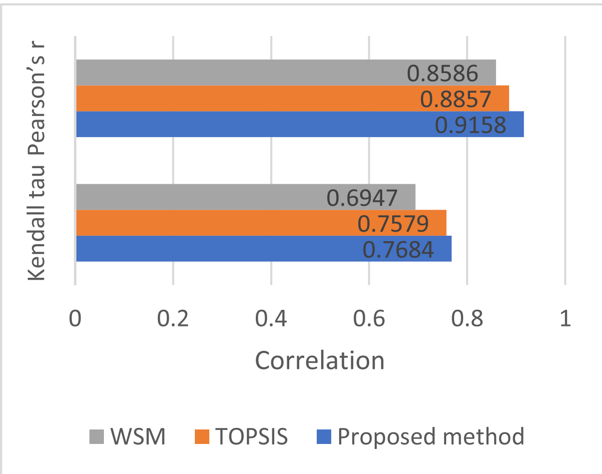

Fig. 7 Bivariate correlation results with TripAdvisor baseline

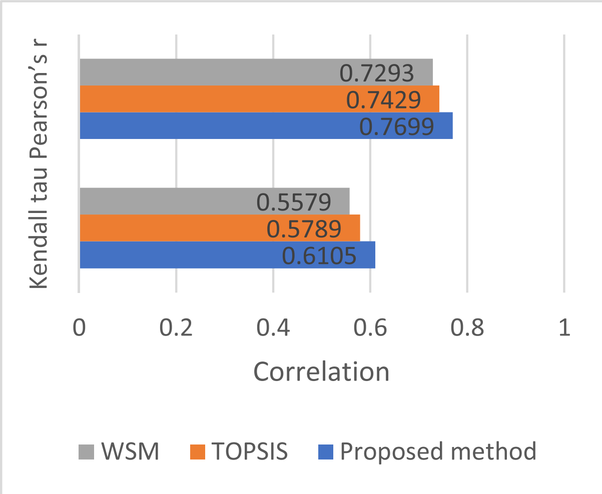

Fig. 8 Bivariate correlation results with star rating baseline

For their study authors had used reviews from 6 users which had posted reviews for all four restaurants, but for our methodology, we used all the available reviews posted by users in the English language for these four restaurants. Rankings obtained from our methodology and SA-MpMcDM are shown in Table 10. We considered TripAdvisor rankings as baseline to find ranking correlations and benchmarking of the performance.

6.3.2 Comparison with SentiRank

In SentiRank, the authors demonstrated their method for two cases. They used the following aspects for both the cases: Price, Food, Service, and Distance. These aspects were mapped to the following aspects in our simulation: Value for money, Food, Service, and Location. We created customers' preferences for our model based on the aspect requirements described by the authors in their work. e.g. in the first case, for the "Distance" aspect the requirement is given as: "the distance to the city center must be as small as possible" so we translated this to the "Location" aspect being "high" since it is a mandatory requirement. In the second case, the "Distance" aspect preference is given as: "restaurants in the city center are preferred". This is translated to "medium" since this is just a preference and not a stringent requirement. Similar translations are done for all the aspects to formulate the following customer preferences:

Table 10 Result comparison of the proposed technique with SA-MpMcDM

Restaurant	Preference Score (proposed method)	Proposed method ranking	SA-MpMcDM ranking	TripAdvisor ranking (baseline)
Oxo Tower	1.492	1	2	1
J. Sheekey	1.474	2	1	2
Wolseley	1.468	3	3	3
Ivy	1.444	4	4	4

Customer preference for case 1:

$$c_{1\mathrm{pref}}(\text{Value for money, Food, Service and Location}) = \{\text{high, high,} \quad \text{low, high}\}$$

Customer preference for case 2:

$$c_{2\mathrm{pref}}(\text{Value for money, Food, Service and Location}) = \{\text{low, high,} \quad \text{low, medium}\}$$

In their work, authors had considered 22 restaurants, but for many of the restaurants, the textual reviews in the English language were either not present or were few in number. For our study, we considered eight restaurants from the list which had at least 30 reviews in English. The rest of the restaurants were removed since they had very few reviews in English. Table 11 shows the restaurants used and ranking outcomes for our approach and SentiRank. The baseline for result comparison was created using star ratings given by users on the aspects used in these cases.

Using Kendall's tau and Pearson's r bivariate correlations were found with baselines as described in earlier comparisons. Table 12 shows the correlations obtained. It can be seen from the table that the proposed method performs better than SA-MpMcDM when simulated with TripAdvisor Restaurants dataset from the city of London. For the restaurant's dataset from Spain: For case 1, the proposed method and SentiRank show similar Kendall's tau correlation, the proposed method is slightly better (0.52 for proposed method vs 0.51 for SentRank). But SentiRank shows a better Pearson's r correlation with baseline as compared to our proposed method. For case 2, the proposed method performed better than SentiRank, showing better Kendall's tau and Pearson's r correlation coefficients with the baseline. The proposed methodology has been designed to incorporate customers' preferences and models linguistic uncertainty in a better way than these existing techniques. The SA-MpMcDM presents no way to model customers' preferences in decision aid whereas SentiRank does use customer preferences but fails to adequately capture linguistic uncertainty. It is can be seen from the table that the proposed methodology gives better results as compared to these methods.

Figures 9 and 10 show viz. a viz. comparison for the proposed method with SA-MpMcDM and SentiRank using Kendall's tau and Pearson's r correlation coefficients. As depicted in these figures, we were able to make better ranking predictions for users as compared to these methods.

Table 11 Result comparison of the proposed technique with SentiRank

Restaurant	Preference Score Case 1	Proposed method ranking for case 1	SentiRank ranking case 1	Preference Score case 2	Proposed method ranking for case 2	SentiRank ranking case 2	Star ratings-based ranks
Tarakon	1.554	1	3	1.603	1	6	2
ELIAN Cafe	1.494	2	1	1.554	2	3	1
Arcs	1.472	3	2	1.541	4	2	3
AQ	1.470	4	4	1.553	3	4	3
Barquet	1.464	5	1	1.534	5	3	4
Les Coques	1.463	6	5	1.531	6	5	6
Sadoll	1.449	7	1	1.525	7	1	2
Ca L Eulalia	1.42	8	6	1.511	8	7	5

Table 12 Bivariate correlation comparison results of the proposed method with SA-MpMcDM and SentiRank

Dataset	Technique	Kendall tau	Pearson's r
TripAdvisor London Restaurants	Proposed method	1.00	1.00
	SA-MpMcDM	0.67	0.8
TripAdvisor Spain Restaurants	Proposed method - case 1	0.52	0.63
	SentiRank - case 1	0.51	0.71
	Proposed method - case 2	0.51	0.62
	SentiRank - case 2	0.33	0.47

7 Conclusion and future scope

This paper presents a novel approach for MCDM, which acts as a decision support system for e-commerce-based product ranking and recommendations. The model presents a unique way to incorporate customers' preferences in the decision-making process. We have addressed two important problems for product rankings, first incorporating the user's preferences for making personalized suggestions, and second, using multiple aspects together to create personalized rankings. The proposed method overcomes two important limitations in existing decision support systems. First, it provides a way to incorporate customers' preferences in decision aid and make varying recommendations based on them. Second, it uses a unique model to deal with linguistic uncertainty found in text using plithogenic sets in multi-criterion decision aid systems. It was shown through experiments how our model created appropriate recommendations for various users.

The efficacy of the model is established by conducting an empirical study. The model is compared with two MCDM techniques, TOPSIS and WSM as well as two latest state-of-the-art methods, SA-MpMcDM and SentiRank. The model performance is demonstrated on two different e-commerce categories namely, Hotel selection and Restaurant selection. In both the categories, the system performs convincingly well and outperforms other techniques.

In the future, we propose to extend this study to other e-commerce product categories. This model can be improved by including textual and NLP capabilities for better capturing users' preferences. While creating this model numerical ratings provided by the users were not taken

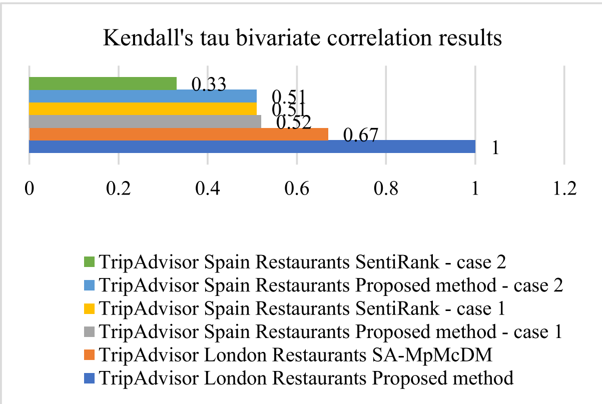

Fig. 9 Comparison of proposed method and other techniques using Kendall's Tau correlation

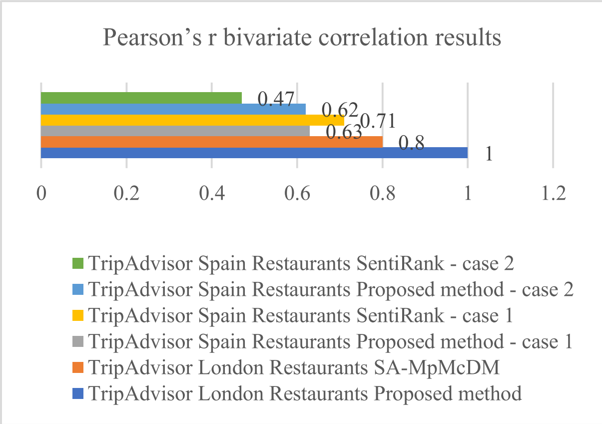

Fig. 10 Comparison of proposed method and other techniques using Pearson's r correlation

into consideration, it needs to be seen how these ratings impact system performance. To further improve the accuracy of our model, we will be exploring other deep learning and machine learning techniques to accomplish ABSA.

Author Contributions Divya Arora: Conceptualization, defining methodology, software evaluation & implementation, validation, result analysis, original draft creation, editing the draft, and article finalization. Prof. Devendra K Tayal, Dr. Sumit K Yadav: Conceptualization, methodology, reviewing the drafts, investigation, and research work supervision.

Data availability The dataset analysed during the current study is available at: https://github.com/DivyaIGDTUW/DataSetTripAdvisor.

Funding No funds and grants was received.

References

1. Abdel-Basset M, Mohamed R (2020) A novel plithogenic TOPSIS-CRITIC model for sustainable supply chain risk management. J Clean Prod 247:119586. https://doi.org/10.1016/j.jclepro.2019.119586
2. Abdel-Basset M, El-Hoseny M, Gamal A, Smarandache F (2019) A novel model for evaluation hospital medical care systems based on plithogenic sets. Artif Intell Med 100:101710. https://doi.org/10.1016/j.artmed.2019.101710
3. Abdel-Basset M, Mohamed R, Zaied AENH, Gamal A, Smarandache F (2020) Solving the supply chain problem using the best-worst method based on a novel Plithogenic model. In: Optimization Theory Based on Neutrosophic and Plithogenic Sets. Academic Press, pp 1–19. https://doi.org/10.1016/B978-0-12-819670-0.00001-9
4. Aghababaei S, Makrehchi M (2016) Mining social media content for crime prediction. In: 2016 IEEE/WIC/ACM international conference on web intelligence (WI), pp. 526-531. https://doi.org/10.1109/WI.2016.0089
5. Ali F, Kwak D, Khan P, Islam SR, Kim KH, Kwak KS (2017) Fuzzy ontology-based sentiment analysis of transportation and city feature reviews for safe traveling. Transp Res C: Emerg Technol 77:33–48. https://doi.org/10.1016/j.trc.2017.01.014
6. Al-Smadi M, Qawasmeh O, Al-Ayyoub M, Jararweh Y, Gupta B (2018) Deep recurrent neural network vs. support vector machine for aspect-based sentiment analysis of Arabic hotels' reviews. J Comput Sci 27:386–393. https://doi.org/10.1016/j.jocs.2017.11.006

7. Atanassov KT (1999) Intuitionistic fuzzy sets. Intuitionistic fuzzy sets. Physica, Heidelberg. https://doi.org/10.1007/978-3-7908-1870-3_1
8. Bi JW, Liu Y, Fan ZP (2019) Representing sentiment analysis results of online reviews using interval type-2 fuzzy numbers and its application to product ranking. Inf Sci 504:293–307. https://doi.org/10.1016/j.ins.2019.07.025
9. Chen L, Yan D, Wang F (2019) User perception of sentiment-integrated critiquing in recommender systems. Int J of Human-Computer Studies 121:4–20. https://doi.org/10.1016/j.ijhcs.2017.09.005
10. Dhingra K, Yadav SK (2019) Spam analysis of big reviews dataset using fuzzy ranking evaluation algorithm and Hadoop. Int J Mach Learn Cybern 10(8):2143–2162. https://doi.org/10.1007/s13042-017-0768-3
11. Guo C, Du Z, Kou X (2018) Products ranking through aspect-based sentiment analysis of online heterogeneous reviews. J Syst Sci Syst Eng 27(5):542–558. https://doi.org/10.1007/s11518-018-5388-2
12. Gupta V, Singh VK, Mukhija P, Ghose U (2019) Aspect-based sentiment analysis of mobile reviews. J Intell Fuzzy Syst 36(5):4721–4730
13. Haider S, Tanvir Afzal M, Asif M, Maurer H, Ahmad A, Abuarqoub A (2018) Impact analysis of adverbs for sentiment classification on twitter product reviews. Concurr Comput: Practice and Experience 33(4): e4956. https://doi.org/10.1002/cpe.4956
14. He K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition 770-778
15. Hung C, Chen SJ (2016) Word sense disambiguation based sentiment lexicons for sentiment classification. Knowl-Based Syst 110:224–232. https://doi.org/10.1016/j.knosys.2016.07.030
16. Jabreel M, Maaroof N, Valls A, Moreno A (2021) Introducing sentiment analysis of textual reviews in a multi-criteria decision aid system. Appl Sci 11(1):216. https://doi.org/10.3390/app11010216
17. Kamel M, Siuky FN, Yazdi HS (2019) Robust sentiment fusion on distribution of news. Multimed Tools Appl 78:21917–21942. https://doi.org/10.1007/s11042-019-7505-8
18. Kendall MG (1938) A new measure of rank correlation. Biometrika 30(1/2):81–93. https://doi.org/10.2307/2332226
19. Koren Y, Bell R, Volinsky C (2009) Matrix factorization techniques for recommender systems. Computer 42(8):30–37. https://doi.org/10.1109/MC.2009.263
20. Kumar G, Parimala N (2020) An integration of sentiment analysis and MCDM approach for smartphone recommendation. Int J Inf Technol Decis Mak 19(04):1037–1063. https://doi.org/10.1142/S021962202050025X
21. Li S, Zha ZJ, Ming Z, Wang M, Chua TS, Guo J, Xu W (2011) Product comparison using comparative relations. In: Proceedings of the 34th international ACM SIGIR conference on research and development in information retrieval, pp. 1151-1152. https://doi.org/10.1145/2009916.2010094
22. Li Q, Wang J, Wang F, Li P, Liu L, Chen Y (2017) The role of social sentiment in stock markets: a view from joint effects of multiple information sources. Multimed Tools Appl 76:12315–12345. https://doi.org/10.1007/s11042-016-3643-4
23. Li L, Yuan H, Qian Y, Shao P (2018) Towards exploring when and what people reviewed for their online shopping experiences. J Syst Sci Syst Eng 27(3):367–393. https://doi.org/10.1007/s11518-016-5318-0
24. Li X, Wu C, Mai F (2019) The effect of online reviews on product sales: a joint sentiment-topic analysis. Inf Manag 56(2):172–184. https://doi.org/10.1016/j.im.2018.04.007
25. Liang Y, Meng F, Zhang J, Xu J, Chen Y, Zhou J (2020) A dependency syntactic knowledge augmented interactive architecture for end-to-end aspect-based sentiment analysis. https://arxiv.org/abs/2004.01951
26. Liu B (2012) Sentiment analysis and opinion mining. Synth Lect Hum Lang Technol 5(1):1–167. https://doi.org/10.2200/S00416ED1V01Y201204HLT016
27. Liu Y, Bi JW, Fan ZP (2017) Ranking products through online reviews: a method based on sentiment analysis technique and intuitionistic fuzzy set theory. Inf Fusion 36:149–161. https://doi.org/10.1016/j.inffus.2016.11.012
28. Liu Y, Bi JW, Fan ZP (2017) A method for ranking products through online reviews based on sentiment classification and interval-valued intuitionistic fuzzy TOPSIS. Int J Inf Technol Decis Mak 16(06):1497–1522. https://doi.org/10.1142/S021962201750033X
29. Liu Y, Jiang C, Zhao H (2019) Assessing product competitive advantages from the perspective of customers by mining user-generated content on social media. Decis Support Syst 123:113079. https://doi.org/10.1016/j.dss.2019.113079
30. Majumder N, Bhardwaj R, Poria S, Gelbukh A, Hussain A (2020) Improving aspect-level sentiment analysis with aspect extraction. Neural Comput Applic:1–11. https://doi.org/10.1007/s00521-020-05287-7
31. Mukhtar N, Khan MA, Chiragh N (2018) Lexicon-based approach outperforms supervised machine learning approach for Urdu sentiment analysis in multiple domains. Telematics Inform 35(8):2173–2183. https://doi.org/10.1016/j.tele.2018.08.003
32. Nassif AB, Elnagar A, Shahin I, Henno S (2021) Deep learning for Arabic subjective sentiment analysis: challenges and research opportunities. Appl Soft Comput 98:106836. https://doi.org/10.1016/j.asoc.2020.106836

33. Ortigosa A, Martín JM, Carro RM (2014) Sentiment analysis in Facebook and its application to e-learning. Comput Hum Behav 31:527–541. https://doi.org/10.1016/j.chb.2013.05.024
34. Öztaş GZ, Adalı EA, Tuş A, Öztaş T, Özçil A (2020) An alternative approach for performance evaluation: Plithogenic sets and DEA. In international conference on intelligent and fuzzy systems, springer, Cham, pp. 742–749. https://doi.org/10.1007/978-3-030-51156-2_86
35. Pazzani MJ, Billsus D (2007) Content-based recommendation systems. The adaptive web:325–341. https://doi.org/10.1007/978-3-540-72079-9_10
36. Pearson K (1896) VII mathematical contributions to the theory of evolution.—III. Regression, heredity, and panmixia. In: Philosophical transactions of the Royal Society of London Series A, containing papers of a mathematical or physical character, 187:253–318. https://doi.org/10.1098/rsta.1896.0007
37. Piryani R, Gupta V, Singh VK, Ghose U (2017) A linguistic rule-based approach for aspect-level sentiment analysis of movie reviews. In: Advances in computer and computational sciences. Springer, Singapore, pp 201–209. https://doi.org/10.1007/978-981-10-3770-2_19
38. Ray A, Bala PK, Dwivedi YK (2021) Exploring values affecting e-learning adoption from the user-generated-content: a consumption-value-theory perspective. J Strateg Mark 29(5):430–452. https://doi.org/10.1080/0965254X.2020.1749875
39. Salama AA, Smarandache F, Kroumov V (2014) Neutrosophic crisp sets & neutrosophic crisp topological spaces. Infinite Study
40. Sarwar B et al (2001) Item-based collaborative filtering recommendation algorithms. In: proceedings of the 10th international conference on world wide web, pp. 285–295. https://doi.org/10.1145/371920.372071
41. Smarandache F (2017) Plithogeny, plithogenic set, logic, probability, and statistics. https://digitalrepository.unm.edu/math_fsp/20
42. Smarandache, F (2018) Plithogenic set, an extension of crisp, fuzzy, intuitionistic fuzzy, and neutrosophic sets-revisited. Infinite Study
43. Stojanovski D, Strezoski G, Madjarov G, Dimitrovski I, Chorbev I (2018) Deep neural network architecture for sentiment analysis and emotion identification of twitter messages. Multimed Tools Appl 77:32213–32242. https://doi.org/10.1007/s11042-018-6168-1
44. Titov I, McDonald R (2008) A joint model of text and aspect ratings for sentiment summarization. In: proceedings of ACL-08: HLT, pp. 308-316. https://www.aclweb.org/anthology/P08-1036.pdf
45. Yu Y, Wang X (2015) World cup 2014 in the twitter world: a big data analysis of sentiments in US sports fans' tweets. Comput Hum Behav 48:392–400. https://doi.org/10.1016/j.chb.2015.01.075
46. Yu J, Zha ZJ, Wang M, Chua TS (2011) Aspect ranking: identifying important product aspects from online consumer reviews. In: Proceedings of the 49th annual meeting of the association for computational linguistics: human language technologies, pp. 1496-1505. https://www.aclweb.org/anthology/P11-1150.pdf
47. Zadeh LA (1965) Fuzzy sets. Inf Control 8:338–353. https://doi.org/10.1016/S0019-9958(65)90241-X
48. Zhang L, Liu B, Lim SH, O'Brien-Strain E (2010) Extracting and ranking product features in opinion documents. In: Proceedings of 23rd International Conference on Computational Linguistics, COLING 2010, Posters; Beijing, China, pp. 1462–1470. https://www.aclweb.org/anthology/C10-2167.pdf
49. Zhang K, Cheng Y, Liao WK, Choudhary A (2011) Mining millions of reviews: a technique to rank products based on importance of reviews. In: Proceedings of the 13th international conference on electronic commerce, pp. 1-8. https://doi.org/10.1145/2378104.2378116
50. Zhang D, Li Y, Wu C (2020) An extended TODIM method to rank products with online reviews under intuitionistic fuzzy environment. J Oper Res Soc 71(2):322–334. https://doi.org/10.1080/01605682.2018.1545519
51. Zhao Y, Qin B, Hu S, Liu T (2010) Generalizing syntactic structures for product attribute candidate extraction. In: Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics, Los Angeles, California, pp 377–380. https://www.aclweb.org/anthology/N10-1059.pdf
52. Zhu X, Guo K, Ren S, Hu B, Hu M, Fang H (2021) Lightweight image super-resolution with expectation-maximization attention mechanism. IEEE Trans Circuits Syst Video Technol 32(3): 1273–1284. https://doi.org/10.1109/TCSVT.2021.3078436
53. Zhu X, Guo K, Fang H, Chen L, Ren S, Hu B (2021) Cross view capture for stereo image super-resolution. IEEE Trans Multimed:1. https://doi.org/10.1109/TMM.2021.3092571
54. Zuheros C, Martínez-Cámara E, Herrera-Viedma E, Herrera F (2021) Sentiment analysis based multi-person multi-criteria decision making methodology using natural language processing and deep learning for smarter decision aid. Case study of restaurant choice using TripAdvisor reviews. Information Fusion 68:22–36. https://doi.org/10.1016/j.inffus.2020.10.019