International Journal of Hospitality Management 91 (2020) 102653

Contents lists available at ScienceDirect

International Journal of Hospitality Management

journal homepage: www.elsevier.com/locate/ijhm

A dynamic decision support system for evaluating peer-to-peer rental accommodations in the sharing economy

Madjid Tavana[a,b,*,1], Sayed Mohammad Hossein Mousavi[c], Hassan Mina[d], Farhad Salehian[d]

[a] Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, PA, 19141, USA
[b] Business Information Systems Department, Faculty of Business Administration and Economics, University of Paderborn, D-33098, Paderborn, Germany
[c] Department of Management, University of Tehran, Tehran, Iran
[d] School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran

ARTICLE INFO

Keywords:
Peer-to-peer rental accommodation
Sharing economy
Preference modeling
Best-worst method
TOPSIS
Fuzzy logic

ABSTRACT

Accommodation accounts for one of the biggest expenses while traveling, and deciding where to stay is often confusing and time-consuming. Fortunately, travelers have more options than ever before because of the substantial growth of the peer-to-peer (P2P) short-term rentals in the sharing economy. Designing a user-friendly system that considers travelers' preferences in choosing the right accommodation can enhance customer satisfaction and increase profitability. We propose a dynamic decision support system based on the theory of multi-criteria decision making to assist travelers in personalizing their preferences and finding quality accommodations in the dominant P2P market that aligns with those preferences. We use the fuzzy best-worst method to measure the intensity of the user's preferences and the fuzzy technique for order of preference by similarity to the ideal solution (TOPSIS) to score and evaluate alternative P2P rental properties. We present a case study in the P2P rental accommodations industry to demonstrate the applicability of the method proposed in this study.

1. Introduction

The leading businesses advancing the concept of sharing economy are no longer newcomers. The hospitality and tourism industry has been dramatically affected by the emergence of peer-to-peer (P2P) rental accommodations in the sharing economy (Rianthong et al., 2016). The P2P companies such as Airbnb and HomeAway are a popular online marketplace for guests to rent homes or rooms according to their individual preferences. The main advantage of these alternatives for guests is the possibility to find affordable accommodation in areas where hotel rooms are costly or hard to find. These companies collect feedback from guests and provide an overall average score of the previous customer ratings, often in the form of one to five stars (Narangajavana and Hu, 2008). Customers are also encouraged to leave their opinions or criticisms in the form of short comments. Some companies such as HotelsCombined, Booking.com, Hotles.com, Love Home Swap, Expedia, and Eroomsplus use multi-criteria scoring systems based on customers' feedback. This feature allows visitors and potential customers to choose alternatives that are closer to their ideal vacation home. Booking.com has gone one step further by filtering customers' comments based on keywords such as location, parking, convenience, and accessibility, among others (Mariani and Borghi, 2018). Despite the recent technological advances in the P2P platforms, no dynamic system has been developed for ranking alternative accommodations based on travelers' preferences. The main purpose of this study is to fill this technological gap by developing a dynamic decision support system (DSS) to rank alternative P2P accommodations according to the travelers' preferences.

We propose a dynamic DSS grounded in the theory of multi-criteria decision-making (MCDM) to assist travelers in utilizing their preferences when looking for quality accommodation in the P2P market. Evaluating P2P accommodations are often difficult for tourists and travelers. Although various recommendation systems have been developed over the last decade to help travelers with choosing a place to stay, these systems rarely consider individual traveler's preferences (Ramzan et al., 2019; Young et al., 2017; Hsu et al., 2012; Loh et al., 2003). Most interactions with the P2P platforms involve sorting and filtering data or database queries. The system returns all the sorted or

* Corresponding author at: Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, PA, 19141, USA.

E-mail addresses: tavana@lasalle.edu (M. Tavana), s.hosseinmousavi@ut.ac.ir (S.M.H. Mousavi), hassan.mina@ut.ac.ir (H. Mina), farhad.salehian@ut.ac.ir (F. Salehian).

[1] Web: http://tavana.us/.

https://doi.org/10.1016/j.ijhm.2020.102653
Received 14 March 2020; Received in revised form 10 August 2020; Accepted 12 August 2020

filtered choices that are related to given queries and overwhelms the travelers with a large number of accommodation alternatives. It is also difficult to evaluate alternatives based on textual reviews, votes, ratings or the number of video views. Searching for the most valuable and relevant content among a large amount of information is often as hard as looking for a needle in a haystack for travelers. The online searches of the P2P platforms for suitable accommodations have become time-consuming due to the presence of a huge amount of online information.

In response, some tourism systems and companies have used importance-performance analysis (IPA) proposed by Martilla and James (1977) to simultaneously analyze attribute performance and attribute importance in relation to the overall performance in the tourism industry (e.g., Deng, 2007; Enright and Newton, 2004). Most often, IPA is used to depict various attributes of recreational facilities or travel destinations on a grid with two dimensions where the importance of each attribute and user satisfaction are plotted on the vertical and horizontal axes, respectively (Oh, 2001). Although IPA has been a valuable tool in the tourism industry, previous studies have identified several important shortcomings with this method. Matzler et al. (2004) show IPA is grounded in two erroneous assumptions. The facts that attribute importance and attribute performance are independent, and the relationship between attribute performance and overall customer satisfaction is symmetrical, are simplistic and impractical assumptions. Oh (2001) and Ryan and Huyton (2002) have demonstrated the relationship between attribute importance, and attribute performance is causal. Furthermore, Ting and Chen (2002) and Matzler et al. (2003) have demonstrated the relationship between attribute performance and overall customer satisfaction is asymmetrical. In addition to the faulty representation in IPA, Bacon (2003) and Abalo et al. (2007) also confirm that the estimated levels of importance in IPA are confusing as the rates and ranks are often very high.

We use the fuzzy best-worst method (BWM) to measure the strength of the user's preferences and the fuzzy technique for order of preference by similarity to the ideal solution (TOPSIS) to evaluate the alternative P2P rental properties according to the travelers' preferences. The fuzzy BWM method has been used to weight the criteria because it has a low number of pairwise comparisons and high consistency (Kannan et al., 2020) and TOPSIS has been used for the ranking purpose because TOPSIS has:

(i) the fewest rank reversals among the most widely used MCDM methods according to simulation comparisons (Zanakis et al., 1998),
(ii) the capability to visually represent the performance measures of all alternatives on attributes on a polyhedron (Shih et al., 2007),
(iii) a scalar value that concurrently considers both the best and worst alternatives (Shih et al., 2007),
(iv) a utility-based foundation capable of comparing each alternative directly in the evaluation matrices (Cheng et al., 2002),
(v) a sound logical framework that mimics the human choice rationale (Shih et al., 2007),
(vi) the ability to identify the best alternative quickly and efficiently (Parkan and Wu, 1999), and
(vii) a straight-forward calculation process that is comprehendible and can be easily implemented with a spreadsheet (Shih et al., 2007).

The DSS proposed in this study is designed to assist travelers in customizing their preferences when looking for quality accommodation in the P2P market. The travelers are presented with a multitude of economic criteria (e.g., price, refund policy), evaluation criteria (e.g., rating score, rating history, review volume), distance criteria (e.g., closeness to the city center, closeness to the airport), neighborhood criteria (e.g., population, crime rate), and property criteria (e.g., pet friendliness, parking). They can then customize their selection criteria by choosing multiple and compatible/conflicting criteria. Conflicting criteria, such as price and crime rate, are typical in evaluating options. The P2P properties are generally more expensive in neighborhoods with a low crime rate. In contrast, some criteria such as price and rating scores are compatible since the P2P properties with high rating scores are generally more expensive than properties with low rating scores. Rating scores have a direct impact on consumer purchase decisions and represent a formidable value for the P2P economy. Several studies have confirmed that higher rating scores translate into price markups (Chattopadhyay and Kumar Mitra, 2020; Yang et al., 2019; Gibbs et al., 2018; Chen and Xie, 2017; Liang et al., 2017; Wang and Nicolau, 2017).

Although various recommendation systems have been developed over the last decade to help travelers with choosing a place to stay, these systems do not consider individual traveler's preferences. Besides, most interactions with the P2P platforms involve information retrieval and searches for the accommodations that match a given query. The system then returns a large number of accommodation alternatives that are related to the query. It is often hard for travelers to find the most valuable and relevant accommodation among a large number of options. The integrated fuzzy BWM-TOPSIS method measures the intensity of the user's preferences and evaluates the alternative P2P rental properties according to the travelers' preferences. In addition, we present a real-world case study of a P2P rental accommodation company to demonstrate the applicability of the proposed framework and DSS with a prototype enhanced with what-if analysis capabilities in a dynamic environment. The remainder of this paper is organized as follows. In Section 2, we review the literature on sharing economy and MCDM selection methods. In Section 3, we present the details of the framework proposed in this study. We present our case study in Section 4 and conclude with our conclusions in Section 5.

2. Literature review

In this section, we present an overview of the literature on the sharing economy (P2P accommodation platforms and P2P selection factors) and MCDM selection methods (best-worst method and TOPSIS method).

2.1. Sharing economy

The sharing economy is a socio-economic model built around the sharing of physical and intellectual resources through technology in many industries, including hospitality, transportation, retailing, entertainment, media, and communication (Mauri et al., 2018; Mody et al., 2019a). The sharing economy stimulates sustainable consumption and promotes a cultural shift from the ownership of resources to sharing resources (Cheng and Foley, 2018; Leismann et al., 2013; Yang et al., 2019). The sharing economy has greatly influenced the tourism and hospitality industry over the past few years as the need for efficient value distribution and social connection fuel the rapid growth of this economic model (Cheng, 2016).

The rapid expansion of the sharing economy has changed the accommodations industry. In addition to Airbnb, several short-term rental players now offer over a million listings, and investments are pouring in. In the new economy, short-term rental space and lodging through platforms such as Airbnb is an alternative to offset the cost of ownership and maintenance (Akbar and Tracogna, 2018; Mody et al., 2019b). Instead of ownership, the consumers in sharing economy platforms rely on collaborative consumption. In the short-term rental business model, the accommodation company maintains an inventory and matches owners with renters and, more specifically, hosts with guests (Cheng et al., 2019). This business model has significantly changed travel patterns by reducing accommodation costs and providing a meaningful social connection with locals. An online P2P marketplace in the hospitality and tourism industry comprises consumers who transact directly with sellers through the marketplace platform maintained by a third party. The transactions between the consumers and sellers in P2P marketplaces involves economic risks. Reputation mechanisms are

developed to manage these risks and encourage trust among the consumers and sellers (Ert and Fleischer, 2019). Xie et al. (2019) have emphasized the importance of trust-building mechanisms in P2P short-term rental platforms.

Zhu et al. (2019) show guests regard online ratings and reviews as important information sources in P2P accommodation decisions. They argue online ratings and reviews signal not only effective P2P operation and management but also facilitate favorable word of mouth that has a positive impact on online accommodation bookings. The online reviews of the seller by consumers are the most common reputation mechanism (Ert et al., 2016). The readers should refer to Prayag and Ozanne (2018); Sainaghi and Baggio (2019), and Belarmino and Koh (2020) for a comprehensive review of P2P accommodation sharing research.

The research on user-generated content (such as online reviews) and marketer-generated content (such as the description of goods or services) for P2P short-term rental show these contents have an enormous impact on consumers' purchasing decisions (Liang et al., 2020). Martin-Fuentes et al. (2018) indicate while P2P classification is usually composed of different criteria, price is the most important feature for predicting an accommodation category, followed by rating score. Price and rating scores are mutually important in the hospitality industry and sharing economy. The rating scores and branded affiliations are widely used in the hospitality industry as a quality signal to support pricing decisions (Abrate et al., 2011; Thrane, 2005). These ratings are used to help the seller synthesize information asymmetries into a single score to frame a quality perception to potential customers before consumption. However, the use of rating scores oversimplifies the quality measure by assuming quality is a single-dimension measure (Archak et al., 2011). Economic theory postulates quality as a multidimensional measure with many attributes (Bowbrick, 2014). Lawani et al. (2019) applied a hedonic spatial autoregressive model to rental prices on Airbnb and found the price is influenced by a multitude of factors (i.e., price range, travel purpose, accompanied people, and expectation before consumption among others). In the absence of branded affiliations, in the sharing economy, property owners must provide additional information to increase the attractiveness and guests' satisfaction before consumption, as suggested in the model proposed in this study. The prospective users have the ability to customize their selection criteria and evaluate the available properties in a market according to their selected criteria before consumption.

2.1.1. P2P accommodation platforms

An individual has dual roles as a guest (traveler) or host (provider) inside the P2P accommodation platforms. The guest is the one who is looking to gain access to rental accommodation, and the host is the one who owns the rental accommodation and rents it out to the guest directly or with the help of a mediator. A mediator is the third party facilitating the transaction between a guest and a host in exchange for a predefined part of the exchanged value. The P2P accommodation platform uses the power of online computer information systems to enable, facilitate, or mediate the sharing of rental accommodation between guests and hosts. The P2P accommodation platforms are user-friendly web-based systems that use collaborative filtering to search, review, and compare alternative accommodations to recommend to guests. The goal of an accommodation platform is to help travelers find the perfect listing—and help hosts find guests who are a great fit for their rental accommodation.

Decision support models and algorithms for P2P accommodation selection have drawn the interest of numerous researchers. The problem is that the existing models cannot address the travelers' preferences on the importance of selection criteria. Alptekin and Büyüközkan (2011) developed a web-based intelligent framework that offers travelers a fast and reliable destination planning platform by integrating a case-based reasoning system with the analytic hierarchy process. Peng et al. (2018) developed a decision support model for travelers utilizing online reviews by introducing probabilistic linguistic term sets to summarize reviews statistically. They used a cloud model and two information fusion tools based on the Heronian mean operator to deal with probabilistic linguistic information. Nave et al. (2018) proposed a DSS with two different dashboards for text mining and sentimental analysis to structure online reviews to help managers develop new opportunities aligned with travelers' expectations. Wang et al. (2020) developed a bounded rationality behavioral DSS with fuzzy information to address hotel selection problems for different travelers (i.e., business, couples, families, friends, and solo) based on key criteria and their importance weights.

Ahani et al. (2019) studied the important factors for accommodation selection based on previous travelers' reviews and developed integrated soft computing and MCDM method to determine the satisfaction and preferences among travelers that affect their decision in selecting a suitable travel accommodation. Ramzan et al. (2019) proposed an intelligent method for dealing with large heterogeneous data to satisfy the needs of the potential travelers by proposing a collaborative filtering recommendation approach. They combined semantic analysis, syntax analysis, and lexical analysis to understand sentiment towards accommodation features and the traveler type (solo, family, couple, etc.). P2P accommodation platforms require multiple interactions between travelers and providers. Park and Tussyadiah (2019) studied the trust between travelers and providers and provided important suggestions and recommendations for trust formation in the P2P accommodation rental marketplace.

2.1.2. P2P selection factors

Previous research has identified various attributes such as value, socialization, communication, authentic experience, and community used by guests for P2P accommodation selection (Guttentag, 2015; Tussyadiah, 2016; Tussyadiah and Pesonen, 2016). Tussyadiah and Zach (2017) used cluster analysis and analyzed P2P accommodation reviews. They identified service, facility, comfort, location, and feel welcome as the most widely considered accommodation attributes in the P2P market. Even though the essential services provided by P2P accommodations are similar to hotels, there are no standard quality classifications or star ratings across the P2P accommodation industry. Besides, there are significant differences between hotels and P2P accommodations. For example, while the location is one of the most important attributes in hotel selection (Lockyer, 2004), it is not significantly important in P2P accommodation selection (Tussyadiah, 2016). Although the attributes identified in these studies are somewhat comparable, knowledge of attributes used by guests to evaluate P2P accommodation is very limited (Tussyadiah and Zach, 2017). In general, the number of P2P accommodation selection attributes exceed those used for hotel selection (Guttentag and Smith, 2017). We studied four major online short-term accommodation rental platforms (i.e., Airbnb, HomeAway, FlipKey, and Onefinestay) and identified the selection criteria used by each platform. As shown in Table 1, there are some similarities and some differences between the accommodation attributes used by the four major P2P accommodation platforms.

2.2. MCDM selection methods

In this study, we use the fuzzy BWM to measure the intensity of the user's preferences and the TOPSIS to evaluate the alternative P2P accommodations according to the travelers' preferences.

2.2.1. Best-worst method

The BWM is a simple but powerful MCDM method based on a systematic pairwise comparison of the multiple and often conflicting criteria (Rezaei, 2015). The process starts by identifying the best and the worst criteria among the criteria set in an MCDM problem. The best criterion is the most important, and the worst criterion is the least important criterion in a decision- making problem. Rezaei (2015) suggests using the terms "best" and "worst" and states that "In an

Table 1
Selection factors for major online short-term accommodation rental platforms.

Selection factor	Airbnb	HomeAway	FlipKey	Onefinestay
Price	✓	✓	✓	✓
Facilities/Amenities	✓	✓	✓	✓
Bedroom	✓	✓	✓	✓
House Rules	✓	✓	✓	✓
Cancellation	✓	✓	✓	✓
Accessibility	✓	✓	✓	✓
Property Type	✓	✓	✓	✓
Location	✓	✓	✓	✓
Family			✓	✓
Neighborhoods	✓	✓		
Activities		✓	✓	
Others	• Host language • Cleanliness • Communication • Check-in • Accuracy • Value • Type of place • Instant book • Unique stays	• Safety • Virtual tour • Property reviews • Booking options • Premier partner	• Suitability • Policies • Rental types • Bathrooms	• Equipment

MCDM problem, a number of alternatives are evaluated with respect to a number of criteria in order to select the best alternative(s). According to BWM, the best (e.g. most desirable, most important) and the worst (e.g. least desirable, least important) criteria are identified first by the decision-maker. Pairwise comparisons are then conducted between each of these two criteria (best and worst) and the other criteria (p. 49)." In other words, the best criterion is the most important criterion, and the worst criterion is the least important criterion in the BWM. The term "worst" is not synonymous with the term "unimportant." It simply means the criterion is "less important" than all other criteria (but is still important). According to the BWM, the unimportant or irrelevant criteria should not be included in the BWM decision matrix.

The decision-maker first compares the best criterion with all other criteria. The decision-maker then compares all criteria with the worst criterion. A predefined scale of 1–9 is used to record the strength of the references. Next, an optimization problem is formulated with these two sets of pairwise comparisons as inputs. The optimal result of this optimization problem is the criteria weights. The significant features of the BWM are less pairwise comparisons and more reliable results. Guo and Zhao (2017) argue that in many real-world MCDM problems, the 1–9 pairwise comparison scale used in the BWM reflects qualitative judgments, which are characterized by uncertainty and ambiguity. They propose fuzzy BWM to model the vague pairwise comparison judgments in BWM. Similarly, we use the fuzzy BWM in this study to measure the vague intensity of the user's preferences for their P2P rental accommodation criteria. The fuzzy BWM has been used in a wide range of real-world problems including service management (Chen et al., 2020), insurance product evaluation (Mi and Liao, 2019), energy planning (Omrani et al., 2018), and organizational group decision making (Hafezalkotob and Hafezalkotob, 2017), among others.

2.2.2. TOPSIS method

TOPSIS is a well-known compensatory MCDM method used to compare a set of alternatives with reference to a positive ideal solution (PIS) known as the ideal alternative, and a negative ideal solution (NIS) known as the nadir alternative. The ideal alternative is a hypothetical alternative with the most desirable outcomes for the evaluation criteria, and the nadir alternative is a hypothetical alternative with the least desirable outcomes for the evaluation criteria. The best alternative in TOPSIS is the one with the shortest geometric distance from the ideal alternative and farthest geometric distance from the nadir alternative (Yoon, 1980; Hwang and Yoon, 1981). TOPSIS is extensively used to solve a variety of tourism and hospitality management problems such as tourist satisfaction measurement (Martin et al., 2019), accommodation selection (Peng et al., 2018), location selection (Ishizaka et al., 2013), tourism destination assessment (Huang and Peng, 2012; Zhang et al., 2011; Hsu et al., 2009), resort ranking (Tseng, 2011), and tourism quality assessment (Benítez et al., 2007; Tsaur et al., 2002), among others.

The BWM method has been integrated with TOPSIS to solve MCDM problems in manufacturing (Sofuoğlu, 2020), green supplier selection (Tian et al., 2018; Lo et al., 2018; Gupta and Barua, 2017), sustainability assessment (Nie et al., 2018; Ren et al., 2017), energy planning (Omrani et al., 2018), performance measurement (Gupta, 2018), and technology assessment (Serrai et al., 2017).

3. Proposed method

In this study, we propose a comprehensive and integrated MCDM method for evaluating online home rentals by considering multiple and often conflicting criteria. The weights of these criteria are considered adjustable since the priority scores are personalized input variables in the proposed framework. The proposed 10-step integrated framework depicted in Fig. 1 is composed of the fuzzy beat-worst-method and TOPSIS:

Step 1 (Choose the destination and extract criteria): The user selects a destination, and a comprehensive set of criteria is constructed based on the historical data and databases of the P2P rental accommodation company.

Step 2 (Select and rate criteria): The potential guest (user) is asked to select the criteria that best suit his/her needs and rate their importance using a 1–5 scale with 1 representing slightly important, 2, 3, 4, and 5 representing extremely important. The scores provided here are used to generate the best and worst criteria. The criterion with the highest score is identified as the "best," and the criterion with the lowest score is identified as the "worst" criteria. An optional filtering module is embedded in this step for those users who wish to filter price, cancelation fee, travel purpose, and the number of accompanied people for a more purposeful search by limiting the number of alternative accommodations proposed by the system.

Step 3 (Determine the optimal fuzzy weights using the fuzzy best-to-others and others-to-best vectors): Pairwise comparisons are then used to compare the "best criterion" selected in Step 2 to all other criteria according to the scale provided in Table 2(a). Let us consider a simple example with four criteria A, B, C, and D presented in Table 2(b). The importance scores of these five criteria are A = 3,

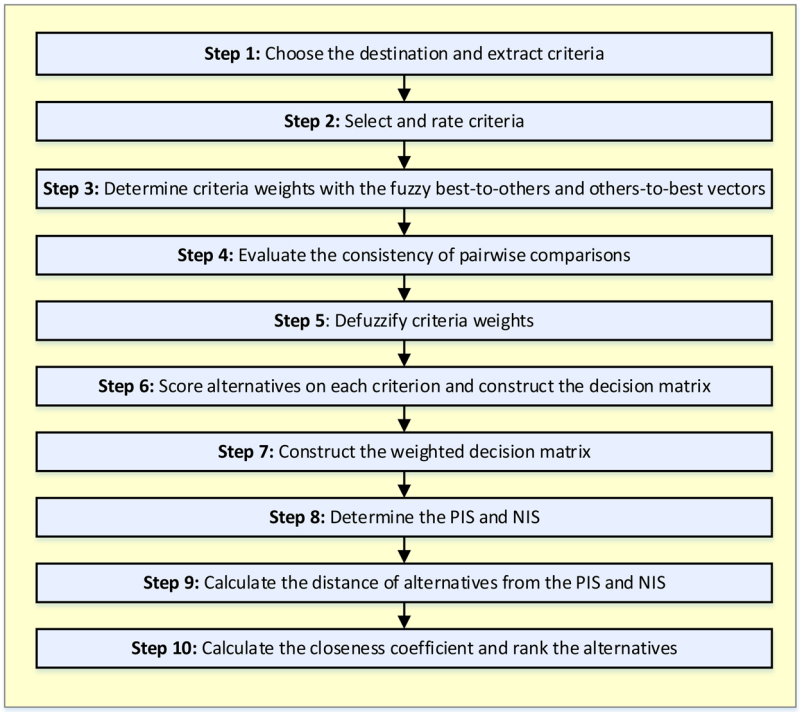

Fig. 1. Proposed framework.

B = 5, C = 2, and D = 4. Criterion B, with the highest score of 5 is identified as the best criterion, and Criterion C, with the lowest score of 2 is identified as the worst criterion. In the best-to-others case, we find the difference between the importance score of the best criterion (Criterion B) to others (Criteria A, C, and D), and find their importance score differences. Table 2(a) is used to match each importance score difference to a linguistic term and triangular fuzzy numbers. Accordingly, a vector of triangular fuzzy numbers is constructed for the best-to-others comparisons. Similarly, a vector of triangular fuzzy numbers is constructed for the others-to-worst comparisons, as shown in Table 2(b).

Next, we find the optimal fuzzy weights of the criteria using the following constrained optimization model proposed by Guo and Zhao (2017).

Notations

j: Criterion j

B: The best criterion

W: The worst criterion

$\widetilde{V}_{Bj}$: The fuzzy Best-to-Others vector

$\widetilde{V}_{jW}$: The fuzzy Others-to-Worst vector

$\tilde{\omega}_B$: The fuzzy weight of the best criterion

$\tilde{\omega}_W$: The fuzzy weight of the worst criterion

$\tilde{\omega}_j$: The fuzzy weight of criterion j

$\tilde{\alpha}$: $Max\left\{\left|\frac{\tilde{\omega}_B}{\tilde{\omega}_j} - \widetilde{V}_{Bj}\right|, \left|\frac{\tilde{\omega}_j}{\tilde{\omega}_W} - \widetilde{V}_{jW}\right|\right\}$

Table 2
Triangular fuzzy numbers for the pairwise comparison differences and an example.

(a). Linguistic terms and their equivalent triangular fuzzy numbers

Difference	Linguistic terms	Triangular fuzzy numbers
0	Indifferent	(1,1,1)
1	Somewhat different	(2/3,1,3/2)
2	Moderately different	(3/2,2,5/2)
3	Very different	(5/2,3,7/2)
4	Extremely different	(7/2,4,9/2)

(b). Simple example

Criteria	Importance score	Best/Worst	Best-to-others			Others-to-worst		
			difference	Linguistic term	Triangular fuzzy numbers vector	difference	Linguistic term	Triangular fuzzy numbers vector
A	3	–	5 – 3 = 2	Moderately different	(3/2,2,5/2)	3 – 2 = 1	Somewhat different	(2/3,1,3/2)
B	5	Best criterion	5 – 5 = 0	indifferent	(1,1,1)	5 – 2 = 3	Very different	(5/2,3,7/2)
C	2	Worst criterion	5 – 2 = 3	Very different	(5/2,3,7/2)	2 – 2 = 0	Indifferent	(1,1,1)
D	4	–	5 – 4 = 1	Somewhat different	(2/3,1,3/2)	4 – 2 = 2	Moderately different	(3/2,2,5/2)

$$\begin{aligned} &Min\ \tilde{\alpha} \\ &s.\ t. \\ &\left|\frac{\tilde{\omega}_B}{\tilde{\omega}_j} - \widetilde{V}_{Bj}\right| \le \tilde{\alpha}\ \forall\, j \\ &\left|\frac{\tilde{\omega}_j}{\tilde{\omega}_W} - \widetilde{V}_{jW}\right| \le \tilde{\alpha}\ \forall\, j \\ &\sum_j R(\tilde{\omega}_j) = 1 \end{aligned} \tag{1}$$

Where each of the parameters or fuzzy variables is represented by three numbers (l, m, u), indicating the pessimistic, most likely, and optimistic states in triangular fuzzy numbers, respectively. Therefore, these parameters and variables are expressed as follows:

$$\begin{aligned} \widetilde{V}_{Bj} &= (l_{Bj}, m_{Bj}, u_{Bj}) \\ \widetilde{V}_{jW} &= (l_{jW}, m_{jW}, u_{jW}) \\ \tilde{\omega}_B &= (l_B^{\omega}, m_B^{\omega}, u_B^{\omega}) \\ \tilde{\omega}_W &= (l_W^{\omega}, m_W^{\omega}, u_W^{\omega}) \\ \tilde{\omega}_j &= (l_j^{\omega}, m_j^{\omega}, u_j^{\omega}) \\ \tilde{\alpha} &= (l^{\alpha}, m^{\alpha}, u^{\alpha}) \end{aligned} \tag{2}$$

Assuming $\tilde{\alpha}^* = (a^*, a^*, a^*)$ and $a^* \le l^{\alpha}$, then the proposed model will be as follows:

$$Min\ a^* \tag{3.1}$$

$$s.t.$$

$$\left|\frac{(l_B^{\omega}, m_B^{\omega}, u_B^{\omega})}{(l_j^{\omega}, m_j^{\omega}, u_j^{\omega})} - (l_{Bj}, m_{Bj}, u_{Bj})\right| \le (a^*, a^*, a^*)\ \ \forall\, j \tag{3.2}$$

$$\left|\frac{(l_j^{\omega}, m_j^{\omega}, u_j^{\omega})}{(l_W^{\omega}, m_W^{\omega}, u_W^{\omega})} - (l_{jW}, m_{jW}, u_{jW})\right| \le (a^*, a^*, a^*)\ \forall\, j \tag{3.3}$$

$$\sum_j R(\tilde{\omega}_j) = 1 \tag{3.4}$$

$$l_j^{\omega} \le m_j^{\omega} \le u_j^{\omega} \tag{3.5}$$

$$l_j^{\omega} \ge 0 \tag{3.6}$$

The objective here is to minimize the maximum absolute differences. According to Guo and Zhao (2017), the optimal weights for criteria are achieved when $\frac{(l_B^{\omega}, m_B^{\omega}, u_B^{\omega})}{(l_j^{\omega}, m_j^{\omega}, u_j^{\omega})} = (l_{Bj}, m_{Bj}, u_{Bj})$ and $\frac{(l_j^{\omega}, m_j^{\omega}, u_j^{\omega})}{(l_W^{\omega}, m_W^{\omega}, u_W^{\omega})} = (l_{jW}, m_{jW}, u_{jW})$. In other words, the maximum absolute differences between $\left|\frac{(l_j^{\omega}, m_j^{\omega}, u_j^{\omega})}{(l_W^{\omega}, m_W^{\omega}, u_W^{\omega})} - (l_{jW}, m_{jW}, u_{jW})\right|$ and $\left|\frac{(l_B^{\omega}, m_B^{\omega}, u_B^{\omega})}{(l_j^{\omega}, m_j^{\omega}, u_j^{\omega})} - (l_{Bj}, m_{Bj}, u_{Bj})\right|$ should be smaller than the objective function given in constraints (3.2) and (3.3), respectively. Constraint (3.4) guarantees that the total weight of the criteria is equal to 1. In triangular fuzzy numbers, the pessimistic weight (i.e. l_j^{ω}) should be smaller than the most likely weight (i.e., m_j^{ω}), and the most likely weight should be smaller than the optimistic weight (i.e., u_j^{ω}). This requirement is enforced by constraint (3.5). Finally, the weight of the criteria should be a positive number, as shown by Constraint (3.6). In this study, the optimal weights of criteria are obtained by implementing this constrained optimization model with a GAMS program.

Step 4 (Evaluate the consistency of pairwise comparisons): In this step, the consistency ratio of the pairwise comparisons is examined by using Eq. (4). The closer the consistency ratio to zero, the greater the consistency is. Table 3 presents the Consistency index for the fuzzy best-worst method.

$$Consistency\ ratio = \frac{q^*}{Consistency\ index} \tag{4}$$

Step 5 (Defuzzify criteria weights): In this step, the fuzzy weights of criteria are deffuzified with Eq. (5).

$$\omega_j = \frac{l_j^{\omega} + 4 \times m_j^{\omega} + u_j^{\omega}}{6} \tag{5}$$

Where ω_j represents the deffuzified weight of criterion j.

Step 6 (Score alternatives on each criterion and construct the decision matrix): In this step, the alternatives are evaluated according to each criterion based on the previous guest's views. Most P2P rental accommodations companies measure the reviewers' (guests') satisfaction with the alternative at play through online questionnaires, often using a 1–10 scale. They then make the guests' simple average scores for each criterion publically available to all customers (Mellinas et al., 2015).

$$DM = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & d_{ij} & \vdots \\ d_{m1} & d_{m2} & \dots & d_{mn} \end{bmatrix} \tag{6}$$

Where d_{ij} is the average score of alternative i for criterion j based on the user's views.

Step 7 (Construct the weighted decision matrix): In this step, the deffuzified weights of criteria obtained in Step 7 are multiplied by the decision matrix constructed in Step 8 to construct the weighted decision matrix. Eq. (7) is used to perform this calculation.

$$\begin{aligned} WDM = \omega_j \times DM &= \begin{bmatrix} \omega_1 \times d_{11} & \omega_2 \times d_{12} & \dots & \omega_n \times d_{1n} \\ \omega_1 \times d_{21} & \omega_2 \times d_{22} & \dots & \omega_n \times d_{2n} \\ \vdots & \vdots & \omega_j \times d_{ij} & \vdots \\ \omega_1 \times d_{m1} & \omega_2 \times d_{m2} & \dots & \omega_n \times d_{mn} \end{bmatrix} \\ &= \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1n} \\ v_{21} & v_{22} & \dots & v_{2n} \\ \vdots & \vdots & v_{ij} & \vdots \\ v_{m1} & v_{m2} & \dots & v_{mn} \end{bmatrix} \end{aligned} \tag{7}$$

Where $v_{ij} = \omega_j \times d_{ij}$.

Step 8 (Determine the PIS and NIS): In this step, the weighted decision matrix and Eq. (8) are used to determine the PIS and the NIS.

$$\begin{aligned} A^* &= (v_1^*, v_2^*, \dots, v_j^*, \dots, v_n^*) \\ A^- &= (v_1^-, v_2^-, \dots, v_j^-, \dots, v_n^-) \end{aligned} \tag{8}$$

Where $v_j^* = \{Max_i(v_{ij}),\ if\ j \in J;\ Min_i(v_{ij}),\ if\ j \in J'\},\ \ \forall\, i, j$ and $v_j^- = \{Min_i(v_{ij}),\ if\ j \in J;\ Max_i(v_{ij}),\ if\ j \in J'\},\ \ \forall\, i, j$. J and J' represent the set of benefits and cost criteria, respectively.

Step 9 (Calculate the distance of alternatives from the PIS and NIS): In this step, Eq. (9) is used to calculate the distance of the alternatives from the PIS and the NIS.

$$\begin{aligned} dis_i^* &= \left(\sum_j (v_{ij} - v_{ij}^*)^2\right)^{0.5},\ \forall\, i = 1, 2, \dots, m \\ dis_i^- &= \left(\sum_j (v_{ij} - v_{ij}^-)^2\right)^{0.5},\ \forall\, i = 1, 2, \dots, m \end{aligned} \tag{9}$$

Step 10 (Calculate the closeness coefficient and rank the alternatives): In the final step, the closeness coefficient (CC_i) of the alternatives are calculated using Eq. 10. The alternatives are then ranked based on their CC_i values in descending order.

$$CC_i = \frac{dis_i^-}{dis_i^* + dis_i^-},\ \forall\, i = 1, 2, \dots, m \tag{10}$$

The approach proposed in this study may seem similar to filtering in MCDM. However, filtering, like the proposed approach, is an expedited search process, but unlike the proposed approach, it performs the search and ranking process based on the keywords or defined constraints. In other words, the filtering process acts as a binary system, and if the alternative does not include the selected keyword, it will not

Table 3
Consistency index for the fuzzy best-worst method.

	Linguistic terms				
	Indifferent	Somewhat different	Moderately different	Very different	Extremely different
$\widetilde{A}_{BW}$	(1,1,1)	(0.667,1,1.5)	(1.5,2,2.5)	(2.5,3,3.5)	(3.5,4,4.5)
Consistency index	3	3.8	5.29	6.69	8.04

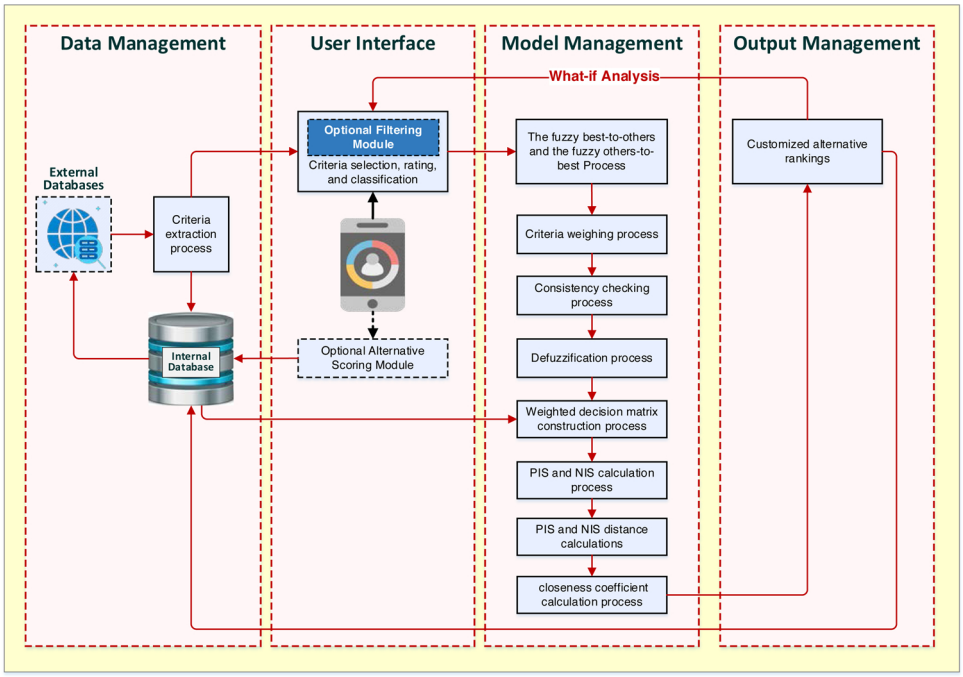

Fig. 2. Proposed DSS.

appear in the search results (i.e., the model is a non-compensatory model). However, in the proposed approach, the alternatives are ranked based on the user's importance weights on each criterion. Consequently, none of the alternatives are eliminated, even if they have a poor performance score on specific criteria (i.e., the model is a compensatory model). The proposed approach not only does not violate the filtering principles but also allows the user to rank the alternatives more purposefully by speeding up the search process and adding filters to the proposed approach.

4. Case study

In this section, we present a simple test case with one user (User A) in Airbnc[2], an American P2P rental accommodations company, to demonstrate the applicability of the method proposed in this study. Airbnc is an online marketplace for arranging short-term rentals primarily as vacation properties. The company does not own any of the properties and acts as a broker receiving commissions from each rental transaction. The company is based in Philadelphia, Pennsylvania. In this case study, we developed a dynamic DSS at Airbnc, which composed of four components, including data management, user interface, model management, and output management, as shown in Fig. 2.

The data management component of this dynamic DSS is used for the criteria extraction process by retrieving data from external databases (market data) as well as Airbnc databases (company data). The user interacts through the user interface component of the DSS in Step 2 for criteria selection and weighing, and in Step 6 for scoring alternative accommodations according to each criterion. The model management component of the DSS then performs all necessary calculations and presents the user with a ranking of alternative rental accommodations based on his/her preferences presented in the output management component of the DSS. The user can then terminate the process (if happy with the recommendation) or perform "what-if analysis" by considering various scenarios (i.e., adding/removing criteria, changing importance weights, removing accommodation alternative, etc.) Next, we explain the 10-step process for User A:

Step 1: In this step, User A chose Paris as the travel destination, and the Airbnc system provided her with a comprehensive set of criteria with relevant data for their accommodation listing. A sample set of 28 criteria divided into five different categories of evaluation, property, neighborhood, economic, and distance factors, is presented in Fig. 3.

In this step, The data from the Airbnb database was used to retrieve a list of potential alternative accommodations in Paris based on six criteria of bathroom amenities, bedroom comfort, cleaning policy, closeness to the city center, price flexibility, and total rating history identified by User A.

Step 2: In this step, User A utilized the optional filtering module to filter price, cancelation fee, travel purpose, and the number of accompanied people for a more purposeful search. The user chose a price range of $200-$299 per night, no cancellation fee, leisure travel, and three accompanied people, as shown in Fig. 4. Next, she considered 28 criteria presented in Fig. 3 and selected the bathroom amenities, bedroom comfort, cleaning policy, closeness to the city center, price flexibility, and total rating history as her selection criteria. She then assigned an importance score to her selected criteria using a 1–5 scoring

[2] The name of the P2P renal accommodations company is changed to protect their anonymity.

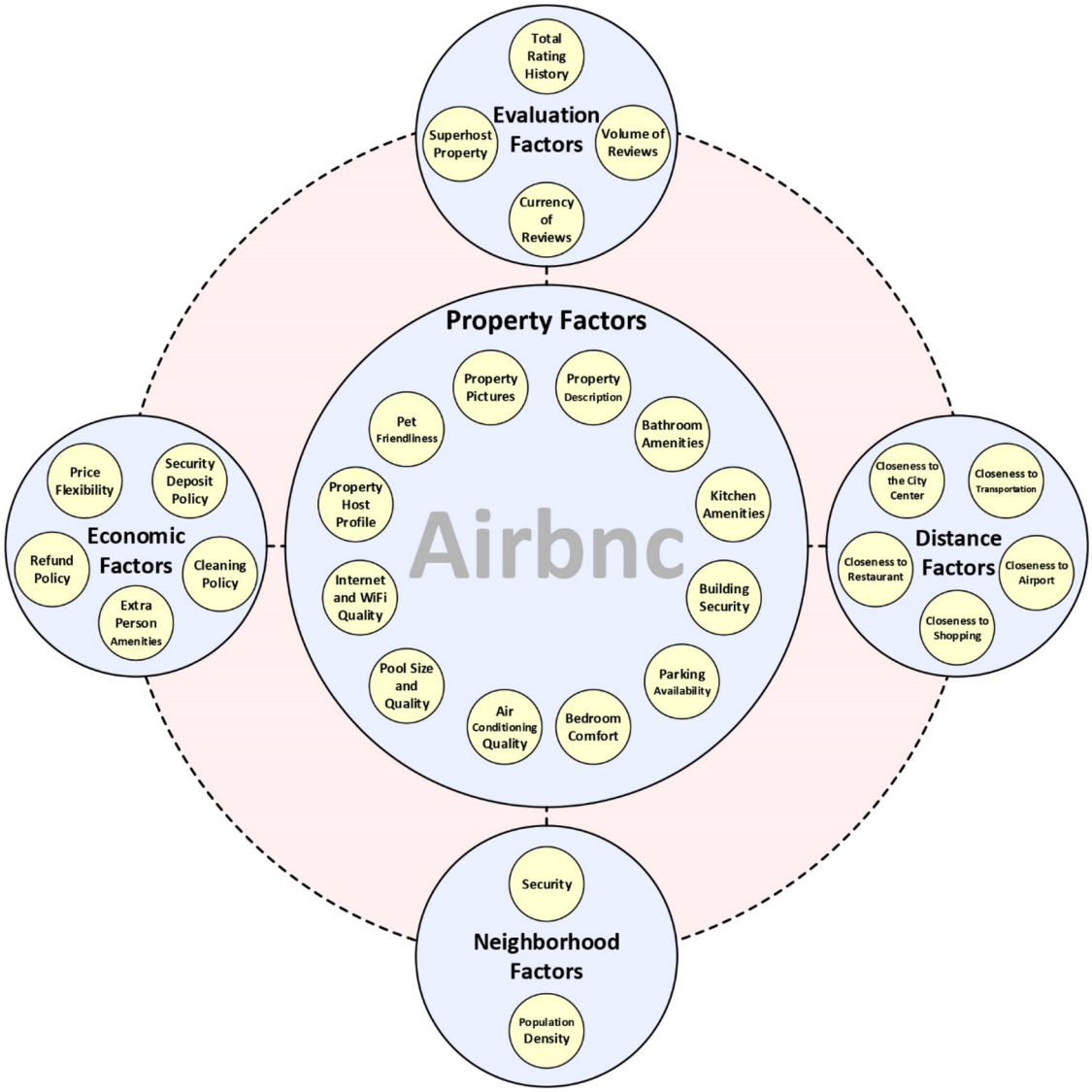

Fig. 3. Proposed framework.

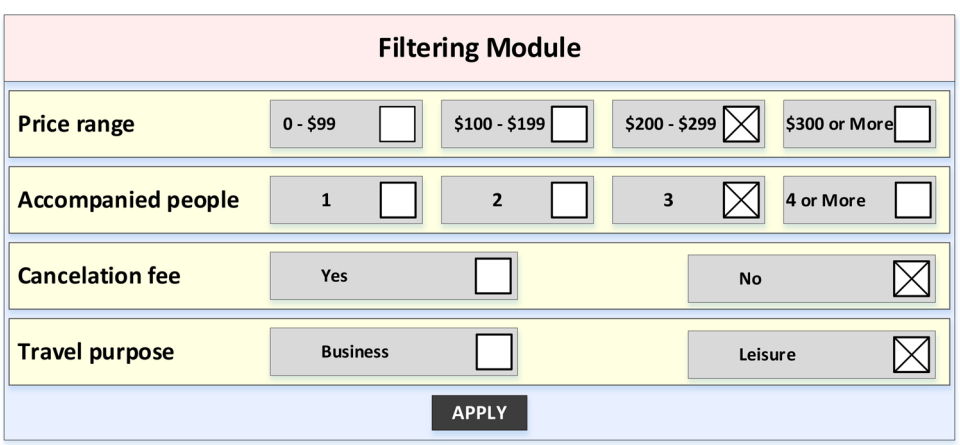

Fig. 4. Filtering module selections for User A.

system. As shown in Table 4, User A, considered the price flexibility criterion as her most important criterion, and the total rating history as her least important criterion.

Step 3: The fuzzy best-to-others and others-to-worst vectors were then calculated according to the pattern presented in Table 5.

Next, the optimal fuzzy criteria weights for User A were calculated using the constraint optimization model proposed by Guo and Zhao (2017). We applied the model to the fuzzy best-to-others and the fuzzy

Table 4
Criteria importance scores for User A.

User	Importance score (1 = Slightly important … 5 = Extremely important)					
	Total rating history	Price flexibility	Closeness to the city center	Cleaning policy	Bedroom comfort	Bathroom amenities
A	1	5	4	3	4	2

Table 5
Fuzzy best-to-others vector and fuzzy others-to-worst vector for User A.

Vector	Criteria					
	Total rating history	Price flexibility	Closeness to the city center	Cleaning policy	Bedroom comfort	Bathroom amenities
Fuzzy best-to-others	(7/2,4,9/2)	(1,1,1)	(2/3,1,3/2)	(3/2,2,5/2)	(2/3,1,3/2)	(5/2,3,7/2)
Fuzzy others-to-worst	(1,1,1)	(7/2,4,9/2)	(5/2,3,7/2)	(3/2,2,5/2)	(5/2,3,7/2)	(2/3,1,3/2)

Table 6
Fuzzy weights of criteria for User A.

Criteria	$(l_j^\omega, m_j^\omega, u_j^\omega)$
Total rating history	(0.073,0.073,0.084)
Price flexibility	(0.269,0.272,0.309)
Closeness to the city center	(0.185,0.209,0.279)
Cleaning policy	(0.110,0.125,0.162)
Bedroom comfort	(0.185,0.209,0.279)
Bathroom amenities	(0.081,0.082,0.096)
$a^* = 0.299$	

Table 7
Consistency ratio for User A.

User	Consistency index	a^*	Consistency ratio
A	8.04	0.299	0.037

Table 8
Defuzzified weights of criteria for User A.

Criteria	$\omega_j = \frac{l_j^\omega + 4 \times m_j^\omega + u_j^\omega}{6}$
Total rating history	0.075
Price flexibility	0.278
Closeness to the city center	0.217
Cleaning policy	0.129
Bedroom comfort	0.217
Bathroom amenities	0.085

others-to-worst vectors and ran the GAMS software with the COUENNE Solver. The following models were constructed for User A:

$$Min\ a^*$$

$$s.t.$$

$$\left|\frac{(l_2^\omega, m_2^\omega, u_2^\omega)}{(l_1^\omega, m_1^\omega, u_1^\omega)} - (\frac{7}{2}, 4, \frac{9}{2})\right| \le (a^*, a^*, a^*)$$

$$\left|\frac{(l_2^\omega, m_2^\omega, u_2^\omega)}{(l_3^\omega, m_3^\omega, u_3^\omega)} - (\frac{2}{3}, 1, \frac{3}{2})\right| \le (a^*, a^*, a^*)$$

$$\left|\frac{(l_2^\omega, m_2^\omega, u_2^\omega)}{(l_4^\omega, m_4^\omega, u_4^\omega)} - (\frac{3}{2}, 2, \frac{5}{2})\right| \le (a^*, a^*, a^*)$$

$$\left|\frac{(l_2^\omega, m_2^\omega, u_2^\omega)}{(l_5^\omega, m_5^\omega, u_5^\omega)} - (\frac{2}{3}, 1, \frac{3}{2})\right| \le (a^*, a^*, a^*)$$

$$\left|\frac{(l_2^\omega, m_2^\omega, u_2^\omega)}{(l_6^\omega, m_6^\omega, u_6^\omega)} - (\frac{5}{2}, 3, \frac{7}{2})\right| \le (a^*, a^*, a^*)$$

$$\left|\frac{(l_3^\omega, m_3^\omega, u_3^\omega)}{(l_1^\omega, m_1^\omega, u_1^\omega)} - (\frac{5}{2}, 3, \frac{7}{2})\right| \le (a^*, a^*, a^*)$$

$$\left|\frac{(l_4^\omega, m_4^\omega, u_4^\omega)}{(l_1^\omega, m_1^\omega, u_1^\omega)} - (\frac{3}{2}, 2, \frac{5}{2})\right| \le (a^*, a^*, a^*)$$

$$\left|\frac{(l_5^\omega, m_5^\omega, u_5^\omega)}{(l_1^\omega, m_1^\omega, u_1^\omega)} - (\frac{5}{2}, 3, \frac{7}{2})\right| \le (a^*, a^*, a^*)$$

$$\left|\frac{(l_6^\omega, m_6^\omega, u_6^\omega)}{(l_1^\omega, m_1^\omega, u_1^\omega)} - (\frac{2}{3}, 1, \frac{3}{2})\right| \le (a^*, a^*, a^*)$$

Table 9
Weighted decision matrix for User A.

Alternatives	Total rating history	Price flexibility	Closeness to the city center	Cleaning policy	Bedroom comfort	Bathroom amenities
AC7	0.615	2.1962	1.6492	0.9804	1.6492	0.7905
AC8	0.6375	2.224	1.6492	1.0449	1.7143	0.7225
AC15	0.5775	2.1128	1.5841	0.9933	1.6058	0.663
AC24	0.5325	2.1962	1.8879	0.8901	1.9096	0.6715
AC29	0.6225	2.0016	1.4322	0.8901	1.4973	0.765
AC36	0.69	2.1406	1.4973	1.1094	1.8228	0.731
AC40	0.7125	2.3908	1.5407	0.9546	1.5407	0.6885
AC52	0.6825	2.502	1.5841	1.1352	1.6492	0.731
AC60	0.6525	1.9182	1.4539	0.8514	1.3671	0.6375
AC64	0.5325	2.4742	2.0398	0.8514	1.8662	0.646
AC66	0.5625	2.5298	1.9313	0.8901	1.953	0.68
AC71	0.69	2.1128	1.5624	1.1352	1.6058	0.765

Table 10
PIS and NIS points for User A.

Ideal/Anti-Ideal	Total rating history	Price flexibility	Closeness to the city center	Cleaning policy	Bedroom comfort	Bathroom amenities
PIS (A^*)	0.7125	2.5298	2.0398	1.1352	1.953	0.7905
NIS (A^-)	0.5325	1.9182	1.4322	0.8514	1.3671	0.6375

Table 11
The distance of alternatives from PIS and NIS for User A.

Alternative	dis^*	dis^-
AC7	0.624196	0.500809
AC8	0.566977	0.562888
AC15	0.746134	0.375142
AC24	0.492830	0.762828
AC29	0.961592	0.223073
AC36	0.683701	0.601228
AC40	0.693854	0.557594
AC52	0.552422	0.745158
AC60	1.080816	0.121946
AC64	0.380064	0.963061
AC66	0.326430	0.985210
AC71	0.723536	0.483119

Table 12
Alternative accommodation rankings for User A and the website.

Alternative	User A		Website	
	CC_i	Rank	Total rating	Rank
AC7	0.445161	8	8.03	5
AC8	0.498190	5	8.10	4
AC15	0.334567	10	7.58	8
AC24	0.607513	3	7.88	7
AC29	0.188300	11	7.48	9
AC36	0.467907	6	8.23	2
AC40	0.445559	7	7.97	6
AC52	0.574268	4	8.40	1
AC60	0.101388	12	7.12	10
AC64	0.717030	2	8.03	5
AC66	0.751128	1	8.23	2
AC71	0.400379	9	8.20	3

Table 13
The revised criteria weights for User A in the "what-if" Scenario 1.

Criteria	$(l_j^\omega, m_j^\omega, u_j^\omega)$	$\omega_j = \frac{l_j^\omega + 4 \times m_j^\omega + u_j^\omega}{6}$
Total rating history	(0.084,0.090,0.096)	0.090
Price flexibility	(0.307,0.342,0.352)	0.338
Cleaning policy	(0.141,0.180,0.217)	0.180
Bedroom comfort	(0.236,0.284,0.318)	0.282
Bathroom amenities	(0.093,0.110,0.129)	0.110

$$\left(\frac{l_1^\omega + 4 \times m_1^\omega + u_1^\omega}{6}\right) + \left(\frac{l_2^\omega + 4 \times m_2^\omega + u_2^\omega}{6}\right) + \left(\frac{l_3^\omega + 4 \times m_3^\omega + u_3^\omega}{6}\right) + \left(\frac{l_4^\omega + 4 \times m_4^\omega + u_4^\omega}{6}\right) + \left(\frac{l_5^\omega + 4 \times m_5^\omega + u_5^\omega}{6}\right) + \left(\frac{l_6^\omega + 4 \times m_6^\omega + u_6^\omega}{6}\right) = 1$$

$$l_1^\omega \le m_1^\omega \le u_1^\omega;\ l_2^\omega \le m_2^\omega \le u_2^\omega;\ l_3^\omega \le m_3^\omega \le u_3^\omega$$
$$l_4^\omega \le m_4^\omega \le u_4^\omega;\ l_5^\omega \le m_5^\omega \le u_5^\omega;\ l_6^\omega \le m_6^\omega \le u_6^\omega$$

$$l_1^\omega, l_2^\omega, l_3^\omega, l_4^\omega, l_5^\omega, l_6^\omega > 0 and a^* > 0$$

We then solved the absolute value equation by splitting the equation and solving the split equations (See Appendix A). We ran a GAMS program with the COUEENE Solver presented in Appendix B to find the optimal fuzzy criteria weights for User A, as shown in Table 6.

Step 4: In this step, we confirmed the consistency of the pairwise comparisons. The consistency ratios were calculated using Eq. (4) and Table 5. The consistency ratios for User A is presented in Table 7. As shown in this table, the consistency ratio for User A is 0.037 (close to zero), confirming the high consistency of the pairwise comparisons.

Step 5: In this step, Eq. (5) was used to defuzzify the fuzzy weights of criteria. The defuzzified weights of criteria for User A are presented in Table 8.

Step 6: In this step, the historical rating scores of the alternative accommodations are retrieved from the database. These rating scores are the collection of previous guests' opinions on each property for each criterion. The Online Supplementary File presents the rating scores of the 73 available accommodations in Paris according to the criteria selected by User A. The optional filtering module used by User A to filter price, cancelation fee, travel purpose, and the number of accompanied people reduced the number of alternative accommodations from 73 to 12. We have highlighted the filtering effect in the Online Supplementary File by identifying the 61 eliminated alternatives, and the remaining 12 alternative accommodations. We should note alternatives, not including at least one of the filters considered by user A, are removed.

Step 7: In this step, we constructed the weighted decision matrix according to Eq. (7) by multiplying the deffuzified weights of criteria in the decision matrix presented in Table 8. The weighted decision matrices for User A is presented in Table 9.

Step 8: In this step, we used Eq. (8) to determine the PIS and the NIS for User A, as shown in Table 10.

Step 9: In this step, we found the alternative distances from the PIS and the NIS for User A, according to Eq. (9), as shown in Table 11.

Step 10: In this step, we used Eq. (10) and calculated the CC_i of the alternatives. The alternatives were then ranked based on their CC_i values in descending order. The ranking of alternatives based on the preferences of User A is presented in Table 12. In addition, the average score of the criteria for each alternative is defined as the website score in Table 12. The system calculates the sum of the criteria ratings and divides it by the number of criteria for calculating the website score for each accommodation. The weights of criteria are considered similarly in this system. Table 13 shows the final ranking of the 12 alternative accommodations in Paris according to the preferences of User A along with the total rating history provided on the Airbnc website. As shown in Table 12, the rankings obtained for both groups (User A and the website) are different from each other in many alternatives.

In this case study, we considered 12 alternatives for ranking. The Airbnc website, on average, offers 73 P2P rental accommodations for each search. As the number of alternative P2P accommodations increases, the decision becomes more cumbersome and time-consuming for the users justifying the need for a dynamic DSS to support users in their decision-making process.

What-if analysis: "What-if" analysis is the process of determining the effects on the outcomes in a model through changes in the input variables and/or assumptions. The prototype developed at Airbnc has a user-friendly interface allowing users to easily change their preferences and receive updated ranking through the output management component of the system. Here, we demonstrate two "what-if" analysis scenarios performed by User A.

- **Scenario 1 (Removing the criterion "closeness to the city**

Table 14
The revised alternative rankings for User A in the "what-if" Scenario 1.

Alternative	Initial solution		Scenario 1 solution		$CC_{scenario} - CC_{initial}$	Percent change	Direction change
	$CC_{initial}$	Rank	$CC_{scenario}$	Rank			
AC7	0.445161	8	0.482152	8	0.0370	8.31%	↑
AC8	0.498190	5	0.563248	6	0.0651	13.06%	↑
AC15	0.334567	10	0.372759	10	0.0382	11.42%	↑
AC24	0.607513	3	0.568473	5	−0.0390	−6.43%	↓
AC29	0.188300	11	0.231166	11	0.0429	22.76%	↑↑
AC36	0.467907	6	0.603555	4	0.1356	28.99%	↑↑
AC40	0.445559	7	0.516571	7	0.0710	15.94%	↑
AC52	0.574268	4	0.693659	2	0.1194	20.79%	↑↑
AC60	0.101388	12	0.110860	12	0.0095	9.34%	↑
AC64	0.717030	2	0.649451	3	−0.0676	−9.42%	↓
AC66	0.751128	1	0.721518	1	−0.0296	−3.94%	↓
AC71	0.400379	9	0.472810	9	0.0724	18.09%	↑

Note: Double arrows represent intense changes > .20 %.

Table 15
The revised criteria weights for User A in the "what-if" Scenario 2.

Criteria	$(l_j^{\omega}, m_j^{\omega}, u_j^{\omega})$	$\omega_j = \frac{l_j^{\omega} + 4 \times m_j^{\omega} + u_j^{\omega}}{6}$
Total rating history	(0.269,0.272,0.309)	0.278
Price flexibility	(0.073,0.073,0.084)	0.075
Closeness to the city center	(0.185,0.209,0.279)	0.217
Cleaning policy	(0.110,0.125,0.162)	0.129
Bedroom comfort	(0.185,0.209,0.279)	0.217
Bathroom amenities	(0.081,0.082,0.096)	0.085

center")

In Scenario 1, User A removed the "closeness to the city center" criterion without changing any importance weights. In response, the system updated the criteria weights with the BWM, as shown in Table 13. Next, by rerunning Steps 6 through 10 of the model, the 12 alternative accommodations were reranked according to their *CC*s, as shown in Table 14. As shown in Table 14, the rankings of five alternatives (AC8, AC24, AC36, AC52, and AC64) were changed. This confirms the sensitivity of the proposed approach to user preferences with three somewhat intense changes of over 20 %.

- **Scenario 2 (Swapping the importance of the "total rating history" and "price flexibility" criteria)**

In Scenario 2, User A swapped the importance rating of the "total rating history" and "price flexibility" criteria while keeping the importance rating of all remaining criteria unchanged. In response, the system updated the criteria weights with the BWM, as shown in Table 15. Next, by rerunning Steps 6 through 10 of the model, the 12 alternative accommodations were reranked according to their *CC*s, as shown in Table 16. As shown in Table 16, the sensitivity of the proposed approach to User A's new preferences is more intense since the ranking of ten alternatives (AC7, AC15, AC24, AC29, AC36, AC52, AC60, AC64, AC66, and AC71) were changed. This confirms the high sensitivity of the proposed approach to user preferences with three somewhat intense changes of over 20 %. In addition, for some alternative accommodations such as AC9 and AC5, the change in their *CC* ratings was significantly large.

5. Conclusion and discussion

The sharing economy and the P2P accommodation rentals have penetrated the hospitality industry and continue to grow at a remarkable pace. Deciding where to stay for business or leisure is often confusing and time-consuming. There are more accommodation options and places to stay than hotels, which allow travelers to relax and feel at home. The review of the sharing economy and the P2P accommodation rental literature shows that the majority of platforms currently used for accommodation selection are based on sorting and filtering data or database queries. One of the disadvantages of these platforms is their inability to take into consideration users' preferences in the search process. Another disadvantage of these platforms is their inability to consider different importance weights for multiple selection criteria. In this study, we proposed the first dynamic DSS that considers users' preferences to conduct a comprehensive and purposeful search of the accommodation rental market. The proposed DSS is composed of a

Table 16
The revised alternative rankings for User A in the "what-if" Scenario 2.

Alternative	Initial solution		Scenario 2 solution		$CC_{scenario} - CC_{initial}$	Percent change	Change
	$CC_{initial}$	Rank	$CC_{scenario}$	Rank			
AC7	0.445161	8	0.446806	9	0.002	0.37%	↑
AC8	0.498190	5	0.523751	5	0.026	5.13%	↑
AC15	0.334567	10	0.313929	11	−0.021	−6.17%	↓
AC24	0.607513	3	0.490068	8	−0.117	−19.33%	↓
AC29	0.188300	11	0.303829	12	0.116	61.35%	↑↑
AC36	0.467907	6	0.579181	1	0.111	23.78%	↑↑
AC40	0.445559	7	0.513543	7	0.068	15.26%	↑
AC52	0.574268	4	0.563356	2	−0.011	−1.90%	↓
AC60	0.101388	12	0.323508	10	0.222	219.08%	↑↑
AC64	0.717030	2	0.518120	6	−0.199	−27.74%	↓↓
AC66	0.751128	1	0.559684	3	−0.191	−25.49%	↓↓
AC71	0.400379	9	0.541502	4	0.141	35.25%	↑↑

Note: Double arrows represent intense changes > .20 %.

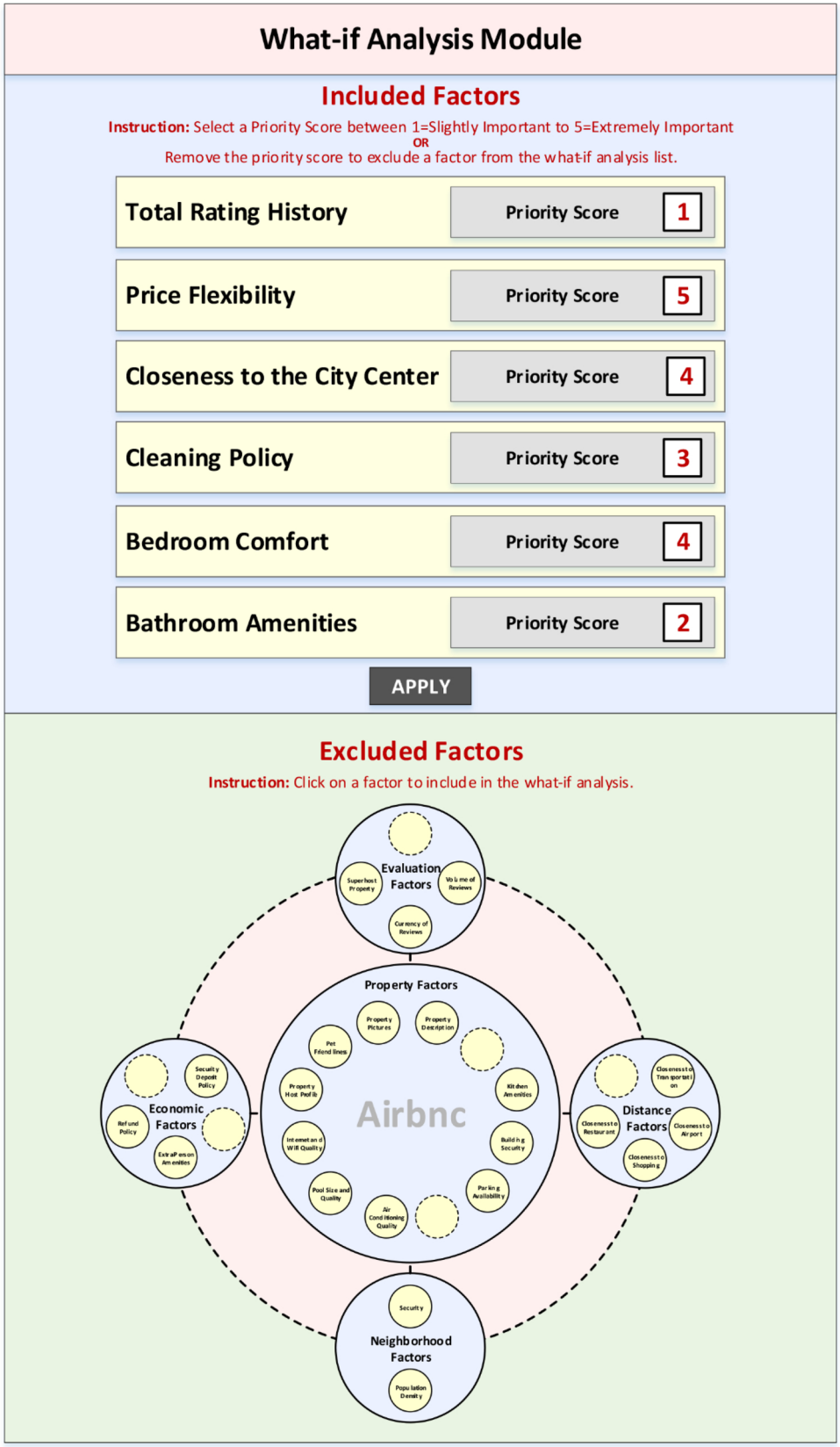

Fig. 5. What-if analysis user interface.

relational data management component, a friendly user interface component, a powerful model management component, and an integrated output management component. The model management component integrates the fuzzy BWM and fuzzy TOPSIS to rank the alternative rental accommodations. We used the fuzzy BWM to measure the strength of the user's preferences and the TOPSIS to score and evaluate alternative P2P accommodations.

5.1. Discussions and interpretations

The proposed P2P system at Airbnc has several unique features for producing efficient and effective searches. Four optional filters on price range, cancelation fee, accompanied people, and travel purpose are used to eliminate dominated alternative accommodations and provide users with a more purposeful search experience. Reducing alternative accommodations improve efficiency and enhance user satisfaction. As shown in the case study, if User A does not use the filtering system, the proposed DSS will provide him/her with 73 alternative accommodations. Because of information overload, the user may have difficulty deciding between 73 alternative accommodations. However, by applying the optional filtering system, the number of alternative accommodations were reduced to 12 properties. Another unique feature of the P2P system at Airbnc is the what-if analysis module capable of determining the effects on the outcomes in a model through changes in the input variables and/or assumptions. The what-if analysis module allows users to easily change their preferences and receive updated ranking through the output management component of the system.

5.2. Theoretical contributions

The theoretical contributions of this study are threefold:

a **Open data theory** refers to sharing information about goods and services through online platforms to increase the value and consumption of those goods and services. Many private and public enterprises are promoting open data initiatives to enable their customers or public more efficient access and use of their products and services. Our system is designed to promote open data and sharing economy.

b **Information overload theory** refers to the difficulty in understanding and processing an issue and effectively making decisions when one has too much information about that issue. Information overload results in tension and cognitive overload, which leads to leads to irritability and poor thinking. Our system is designed to avoid information overload in decision making by minimizing the number of alternative accommodations based on user preferences.

c **Autonomous decision systems theory** refers to the process of making decisions by automated means through DSSs with minimal human intervention. Autonomous decision systems can lead to efficient and consistent decisions, particularly when a very large volume of data needs to be analyzed quickly in dynamic environments. Our system is designed to use minimum human judgments compared to the existing DSSs with conventional multi-criteria decision models requiring multi-layer judgments and pairwise comparisons.

5.3. Practical implications

There are two types of user experiences on the online P2P platform markets: peer providers who list their accommodations, and peer customers who search for accommodations. The practical benefits of the proposed system for the peer customer are the ability to reduce the solution space and avoid information overload through filtering, the ability to select personalized criteria and importance weights through customization, and the ability to ask what-if questions through sensitivity analysis. Conducting purposeful searches with the filtering, personalization, and what-if capabilities are positive experiences that are at the core of customer satisfaction in the P2P accommodation rental industry. These capabilities embedded in the proposed system are designed to produce successful searches and minimize problems such as customer cancellations, product not as described, or additional charges sought, among others. Another important feature of the proposed system is user-friendliness. The user interface for the Airbnc system is simple and intuitive. A typical user can operate the program online with no training. Fig. 5 presents the user interface for the what-if analysis module. As shown in this figure, the user can simply click on a factor to include it in the what-if analysis scenario by assigning a priority score between 1–5, as described in Step 3. A factor in the what-if analysis dialog box can be simply excluded from the analysis by simply removing its priority score. We suggest practicing managers keep the interface simple, use common user interface elements (i.e., checkboxes, dropdown lists), be purposeful in page layout, and use color and texture strategically and effectively in user interface design.

Airbnc, like other accommodation platforms, does not own the property listed on its platform. It provides a marketplace for customers to do business with providers. The most important aspect of Airbnc's business model is that it must attract both peer customers and peer providers. High levels of customer satisfaction and provider positive experience are strong predictors of loyalty, retention, and repurchase for Airbnc.

5.4. Future research directions

Most technological innovations and new approaches suffer from limitations. Focusing on these limitations can pave the way for future research. This study is no exception. In this paper, the interdependencies and causal relationships among criteria have not been taken into consideration while calculating the criteria weights. Considering the interdependencies between the selection criteria using methods such as the decision making trial and evaluation laboratory (DEMATEL), or considering the causal relationships between the selection criteria with methods such as the weighted influence non-linear gauge system (WINGS) are promising areas for continued and future research. Furthermore, the DSS proposed in this study is designed for single decision-makers. Another future research direction is to design and develop a group DSS for P2P rental accommodation decisions involving multiple decision-makers. Finally, we encourage researchers to design and develop negotiation support systems to improve communication and negotiation between peer customers and peer providers in the P2P accommodation rental industry.

Declaration of Competing Interest

The authors report no declarations of interest.

Acknowledgment

Dr. Madjid Tavana is grateful for the partial support he received from the Czech Science Foundation (GAˇCR19-13946S) for this research.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ijhm.2020.102653.

References

Abalo, J., Varela, J., Manzano, V., 2007. Importance values for Importance–performance Analysis: a formula for spreading out values derived from preference rankings. J. Bus. Res. 60 (2), 115–121.

Abrate, G., Capriello, A., Fraquelli, G., 2011. When quality signals talk: evidence from the Turin hotel industry. Tour. Manag. 32 (4), 912–921.

Ahani, A., Nilashi, M., Yadegaridehkordi, E., Sanzogni, L., Tarik, A.R., Knox, K., et al., 2019. Revealing customers' satisfaction and preferences through online review analysis: the case of Canary Islands hotels. J. Retail. Consum. Serv. 51, 331–343.

Akbar, Y.H., Tracogna, A., 2018. The sharing economy and the future of the hotel industry: transaction cost theory and platform economics. Int. J. Hosp. Manag. 71, 91–101.

Alptekin, G.I., Büyüközkan, G., 2011. An integrated case-based reasoning and MCDM system for Web based tourism destination planning. Expert Syst. Appl. 38 (3), 2125–2132.

Archak, N., Ghose, A., Ipeirotis, P.G., 2011. Deriving the pricing power of product features by mining consumer reviews. Manage. Sci. 57 (8), 1485–1509.

Bacon, D.R., 2003. A comparison of approaches to importance-performance analysis. Int. J. Mark. Res. 45 (1), 1–15.
Belarmino, A., Koh, Y., 2020. A critical review of research regarding peer-to-peer accommodations. Int. J. Hosp. Manag. 84, 102315.
Benítez, J.M., Martín, J.C., Román, C., 2007. Using fuzzy number for measuring quality of service in the hotel industry. Tour. Manag. 28 (2), 544–555.
Bowbrick, P., 2014. The Economics of Quality, Grades and Brands. Routledge, London, UK.
Chattopadhyay, M., Kumar Mitra, S., 2020. What Airbnb Host Listings Influence Peer-to-Peer Tourist Accommodation Price? J. Hosp. Tour. Res. 44, 597–623.
Chen, Y., Xie, K.L., 2017. Consumer valuation of Airbnb listings: a hedonic pricing approach. Int. J. Contemp. Hosp. Manage. 29 (9), 2405–2425.
Chen, Z., Ming, X., Zhou, T., Chang, Y., Sun, Z., 2020. A hybrid framework integrating rough-fuzzy best-worst method to identify and evaluate user activity-oriented service requirement for smart product service system. J. Clean. Prod. 253, 119954.
Cheng, M., 2016. Sharing economy: a review and agenda for future research. Int. J. Hosp. Manag. 57, 60–70.
Cheng, M., Foley, C., 2018. The sharing economy and digital discrimination: the case of Airbnb. Int. J. Hosp. Manag. 70, 95–98.
Cheng, S., Chan, C.W., Huang, G.H., 2002. Using multiple criteria decision analysis for supporting decision of solid waste management. J. Environ. Sci. Health Part A 37 (6), 975–990.
Cheng, X., Fu, S., Sun, J., Bilgihan, A., Okumus, F., 2019. An investigation on online reviews in sharing economy driven hospitality platforms: a viewpoint of trust. Tour. Manag. 71, 366–377.
Deng, W., 2007. Using a revised importance–performance analysis approach: the case of Taiwanese hot springs tourism. Tour. Manag. 28 (5), 1274–1284.
Enright, M.J., Newton, J., 2004. Tourism destination competitiveness: a quantitative approach. Tour. Manag. 25 (6), 777–788.
Ert, E., Fleischer, A., 2019. The evolution of trust in Airbnb: a case of home rental. Ann. Tour. Res. 75, 279–287.
Ert, E., Fleischer, A., Magen, N., 2016. Trust and reputation in the sharing economy: the role of personal photos in Airbnb. Tour. Manag. 55, 62–73.
Gibbs, C., Guttentag, D., Gretzel, U., Morton, J., Goodwill, A., 2018. Pricing in the sharing economy: a hedonic pricing model applied to Airbnb listings. J. Travel Tour. Mark. 35 (1), 46–56.
Guo, S., Zhao, H., 2017. Fuzzy best-worst multi-criteria decision-making method and its applications. Knowledge Based Syst. 121, 23–31.
Gupta, H., 2018. Assessing organizations performance on the basis of GHRM practices using BWM and Fuzzy TOPSIS. J. Environ. Manage. 226, 201–216.
Gupta, H., Barua, M.K., 2017. Supplier selection among SMEs on the basis of their green innovation ability using BWM and fuzzy TOPSIS. J. Clean. Prod. 152, 242–258.
Guttentag, D., 2015. Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. Curr. Issues Tour. 18 (2), 1192–1217.
Guttentag, D.A., Smith, S.L.J., 2017. Assessing Airbnb as a disruptive innovation relative to hotels: substitution and comparative performance expectations. Int. J. Hosp. Manag. 64, 1–10.
Hafezalkotob, A., Hafezalkotob, A., 2017. A novel approach for combination of individual and group decisions based on fuzzy best-worst method. Appl. Soft Comput. 59, 316–325.
Hsu, T.K., Tsai, Y.F., Wu, H.H., 2009. The preference analysis for tourist choice of destination: a case study of Taiwan. Tour. Manag. 30 (2), 288–297.
Hsu, F.M., Lin, Y.T., Ho, T.K., 2012. Design and implementation of an intelligent recommendation system for tourist attractions: the integration of EBM model, Bayesian network and Google Maps. Expert Syst. Appl. 39 (315), 3257–3264.
Huang, J.H., Peng, K.H., 2012. Fuzzy Rasch model in TOPSIS: a new approach for generating fuzzy numbers to assess the competitiveness of the tourism industries in Asian countries. Tour. Manag. 33 (2), 456–465.
Hwang, C.L., Yoon, K., 1981. Multiple Attribute Decision Making: Method and Application. Spring-verlag, New York.
Ishizaka, A., Nemery, P., Lidouh, K., 2013. Location selection for the construction of a casino in the Greater London region: a triple multi-criteria approach. Tour. Manag. 34, 211–220.
Kannan, D., Mina, H., Nosrati-Abarghooee, S., Khosrojerdi, G., 2020. Sustainable circular supplier selection: a novel hybrid approach. Sci. Total Environ. 722 137936-137936.
Lawani, A., Reed, M.R., Mark, T., Zheng, Y., 2019. Reviews and price on online platforms: Evidence from sentiment analysis of Airbnb reviews in Boston. Reg. Sci. Urban Econ. 75, 22–34.
Leismann, K., Schmitt, M., Rohn, H., Baedeker, C., 2013. Collaborative consumption: towards a resource-saving consumption culture. Resources 2 (3), 184–203.
Liang, S., Schuckert, M., Law, R., Chen, C.C., 2017. Be a 'superhost': the importance of badge systems for peer-to-peer rental accommodations. Tour. Manag. 60, 454–465.
Liang, S., Schuckert, M., Law, R., Chen, C.C., 2020. The importance of marketer-generated content to peer-to-peer property rental platforms: evidence from Airbnb. Int. J. Hosp. Manag. 84, 102329.
Lo, H.W., Liou, J.J.H., Wang, H.S., Tsai, Y.S., 2018. An integrated model for solving problems in green supplier selection and order allocation. J. Clean. Prod. 190, 339–352.
Lockyer, T., 2004. Weekend Accommodation - The Challenge: What are the Guests Looking for? J. Hosp. Tour. Manag. 11 (1), 1–12.
Loh, S., Lorenzi, F., Saldana, R., Licthnow, D., 2003. A tourism recommendation system based on collaboration and text analysis. Inf. Technol. Tour. 5, 157–165.
Mariani, M.M., Borghi, M., 2018. Effects of the Booking. Com rating system: bringing hotel class into the picture. Tour. Manag. 66, 47–52.
Martilla, J.A., James, J.C., 1977. Importance-performance analysis. J. Mark. 41 (1), 77–79.
Martin, J.C., Saayman, M., du Plessis, E., 2019. Determining satisfaction of international tourist: a different approach. J. Hosp. Tour. Manag. 40, 1–10.
Martin-Fuentes, E., Fernandez, C., Mateu, C., Marine-Roig, E., 2018. Modelling a grading scheme for peer-to-peer accommodation: stars for Airbnb. Int. J. Hosp. Manag. 69, 75–83.
Matzler, K., Sauerwein, E., Heischmidt, K.A., 2003. Importance–performance analysis revisited: the role of the factor structure of customer satisfaction. Serv. Ind. J. 23 (2), 112–129.
Matzler, K., Bailom, F., Hinterhuber, H.H., Renzl, B., Pichler, J., 2004. The asymmetric relationship between attribute-level performance and overall customer satisfaction: a reconsideration of the importance–performance analysis. Ind. Mark. Manag. 33, 271–277.
Mauri, A.G., Minazzi, R., Nieto-García, M., Viglia, G., 2018. Humanize your business. The role of personal reputation in the sharing economy. Int. J. Hosp. Manag. 73, 36–43.
Mellinas, J.P., María-Dolores, S.M.M., García, J.J.B., 2015. Booking. com: the unexpected scoring system. Tour. Manag. 49, 72–74.
Mi, X., Liao, H., 2019. An integrated approach to multiple criteria decision making based on the average solution and normalized weights of criteria deduced by the hesitant fuzzy best worst method. Comput. Ind. Eng. 133, 83–94.
Mody, M., Suess, C., Lehto, X., 2019a. Going back to its roots: can hospitableness provide hotels competitive advantage over the sharing economy? Int. J. Hosp. Manag. 76, 286–298.
Mody, M., Suess, C., Lehto, X., 2019b. Using segmentation to compete in the age of the sharing economy: Testing a core-periphery framework. Int. J. Hosp. Manag. 78, 199–213.
Narangajavana, Y., Hu, B., 2008. The relationship between the hotel rating system, service quality improvement, and hotel performance changes: a canonical analysis of hotels in Thailand. J. Qual. Assur. Hosp. Tour. 9 (1), 34–56.
Nave, M., Rita, P., Guerreiro, J., 2018. A decision support system framework to track consumer sentiments in social media. J. Hosp. Mark. Manage. 27 (6), 693–710.
Nie, R.X., Tian, Z.P., Wang, J.Q., Zhang, H.Y., Wang, T.I., 2018. Water security sustainability evaluation: applying a multistage decision support framework in industrial region. J. Clean. Prod. 196, 1681–1704.
Oh, H., 2001. Revisiting importance–performance analysis. Tour. Manag. 22 (6), 617–627.
Omrani, H., Alizadeh, A., Emrouznejad, A., 2018. Finding the optimal combination of power plants alternatives: a multi response Taguchi-neural network using TOPSIS and fuzzy best-worst method. J. Clean. Prod. 203, 210–223.
Park, S., Tussyadiah, I.P., 2019. How guests develop trust in hosts: an investigation of trust formation in P2P accommodation. J. Travel. Res. https://doi.org/10.1177/0047287519884654. Online First.
Parkan, C., Wu, M.-L., 1999. Decision-making and performance measurement models with applications to robot selection. Comput. Ind. Eng. 36 (3), 503–523.
Peng, H.G., Zhang, H.Y., Wang, J.Q., 2018. Cloud decision support model for selecting hotels on TripAdvisor.com with probabilistic linguistic information. Int. J. Hosp. Manag. 68, 124–138.
Prayag, G., Ozanne, L.K., 2018. A systematic review of peer-to-peer (P2P) accommodation sharing research from 2010 to 2016: progress and prospects from the multi-level perspective. J. Hosp. Mark. Manage. 27 (6), 649–678.
Ramzan, B., Bajwa, I.S., Jamil, N., Ul Amin, R., Ramzan, S., Mirza, F., Sarwar, N., 2019. An intelligent data analysis for recommendation systems using machine learning. Sci. Program. 5941096, 20. https://doi.org/10.1155/2019/5941096.
Ren, J., Liang, H., Chan, F.T.S., 2017. Urban sewage sludge, sustainability, and transition for Eco-City: multi-criteria sustainability assessment of technologies based on best-worst method. Technol. Forecast. Soc. Change 116, 29–39.
Rezaei, J., 2015. Best-worst multi-criteria decision-making method. Omega 53, 49–57.
Rianthong, N., Dumrongsiri, A., Kohda, Y., 2016. Optimizing customer searching experience of online hotel booking by sequencing hotel choices and selecting online reviews: a mathematical model approach. Tourism Manage. Perspect. 20, 55–65.
Ryan, C., Huyton, J., 2002. Tourists and aboriginal people. Ann. Tour. Res. 29 (3), 631–647.
Sainaghi, R., Baggio, R., 2019. Clusters of topics and research designs in peer-to-peer accommodation platforms. Int. J. Hosp. Manag. 102393. https://doi.org/10.1016/j.ijhm.2019.102393.
Serrai, W., Abdelli, A., Mokdad, L., Hammal, Y., 2017. Towards an efficient and a more accurate web service selection using MCDM methods. J. Comput. Sci. 22, 253–267.
Shih, H.S., Shyur, H.J., Lee, E.S., 2007. An extension of TOPSIS for group decision making. Math. Comput. Model. 45 (7–8), 801–813.
Sofuoğlu, M.A., 2020. Fuzzy applications of Best–worst method in manufacturing environment. Soft comput. 24, 647–659.
Thrane, C., 2005. Hedonic price models and sun-and-beach package tours: the Norwegian case. J. Travel. Res. 43 (3), 302–308.
Tian, Z.P., Zhang, H.Y., Wang, J.Q., Wang, T.L., 2018. Green supplier selection using improved TOPSIS and best-worst method under intuitionistic fuzzy environment. Informatica 29 (4), 773–800.
Ting, S.C., Chen, C.N., 2002. The asymmetrical and non-linear effects of store quality attributes on customer satisfaction. Total. Qual. Manag. 13 (4), 547–569.
Tsaur, S.H., Chang, T.Y., Yen, C.H., 2002. The evaluation of airline service quality by fuzzy MCDM. Tour. Manag. 23 (2), 107–115.
Tseng, M.L., 2011. Using hybrid MCDM to evaluate the service quality expectation in linguistic preference. Appl. Soft Comput. 11, 4551–4562.
Tussyadiah, I.P., 2016. Factors of satisfaction and intention to use peer-to-peer accommodation. Int. J. Hosp. Manag. 55, 70–80.
Tussyadiah, I.P., Pesonen, J., 2016. Impacts of peer-to-Peer accommodation use on travel patterns. J. Travel. Res. 55 (8), 1022–1040.
Tussyadiah, I.P., Zach, F., 2017. Identifying salient attributes of peer-to-peer

accommodation experience. J. Travel Tour. Mark. 34 (5), 636–652.
Wang, D., Nicolau, J.L., 2017. Price determinants of sharing economy based accommodation rental: a study of listings from 33 cities on Airbnb.cOm. Int. J. Hosp. Manag. 62, 120–131.
Wang, L., Wang, X.K., Peng, J.J., Wang, J.Q., 2020. The differences in hotel selection among various types of travellers: a comparative analysis with a useful bounded rationality behavioural decision support model. Tour. Manag. 76, 103961.
Xie, K., Mao, Z.E., Wu, J., 2019. Learning from peers: the effect of sales history disclosure on peer-to-peer short-term rental purchases. Int. J. Hosp. Manag. 76, 173–183.
Yang, S.B., Lee, K., Lee, H., Koo, C., 2019. In Airbnb we trust: understanding consumers' trust-attachment building mechanisms in the sharing economy. Int. J. Hosp. Manag. 83, 198–209.
Yoon, K., 1980. Systems Selection by Multiple Attributes Decision Making. PhD Dissertation. Kansas State University, Manhattan, Kansas.
Young, C., Corsun, D., Xie, K., 2017. Travelers' preferences for peer-to-peer (P2P) accommodations and hotels. Int. J. Cult. Tour. Hosp. Res. 11 (4), 465–482.
Zanakis, S.H., Solomon, A., Wishart, N., Dublish, S., 1998. Multi-attribute decision making: a simulation comparison of selection methods. Eur. J. Oper. Res. 107, 507–529.
Zhang, H., Gu, C.L., Gu, L.W., Zhang, Y., 2011. The evaluation of tourism destination competitiveness by TOPSIS & information entropy – a case in the Yangtze River Delta of China. Tour. Manag. 32 (2), 443–451.
Zhu, L., Lin, Y., Cheng, M., 2019. Sentiment and guest satisfaction with peer-to-peer accommodation: When are online ratings more trustworthy? Int. J. Hosp. Manag. 102369. https://doi.org/10.1016/j.ijhm.2019.102369.