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B2C Marketplace Prioritization Using Hesitant Fuzzy Linguistic AHP

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Abstract Commercial Internet rapidly developed through Business to Customer (B2C) businesses since 1990s. B2C provides free online services and discounted shopping to customers. There are lots of B2C firm alternatives in the internet for a customer who seeks for a profitable business. The selection among these B2C alternatives is a multi-attribute decision-making problem with many tangible and intangible criteria under vagueness and impreciseness. In this paper, we propose a hesitant fuzzy linguistic analytic hierarchy process method for the selection among B2C firms. Hesitant fuzzy linguistic term sets are used for the assessments in the pairwise comparison matrices. An ordered weighted averaging operator is used for aggregation operator. A sensitivity analysis is also given to check the robustness of the obtained result.

Keywords Marketplace · B2C · Hesitant fuzzy sets · AHP · OWA · HFLTS

1 Introduction

Digitization of commerce has a vital part in today's economy. Customers can easily find alternative products in electronic marketplaces which indeed form a highly competitive environment for all businesses [50]. On the one hand, digitization brings various new tools for companies to reach customers but on the other hand, it brings various challenges because of competition. An alternative e-commerce channel is using e-marketplaces, which is an electronic space where sellers and buyers meet and conduct different types of transactions including buying, selling and exchange of information. While the functions of an e-marketplace are the same as those of a physical one, digital systems provide more efficiency by providing more updated information and various support services, and easy executions of transactions.

Turban et al. [45] defined three main functions of an e-marketplace as matching of buyers and sellers, facilitation of transactions and institutional infrastructure. The sub-functions listed under matching of buyers and sellers are determination of product offerings, aggregation of different products, search functionality for each party, information publication about the price and details of a product and matching the seller's offerings with the buyer's preferences, and comparison of the product prices. The second group, facilitation of transactions, is composed of sub-functions such as communication between buyers and sellers, informs of posting request for proposal, or posting buyers' requests, delivery of information, goods or services to buyers, transfer of payments to sellers, escrow services, and finally publishing a rating system that show the reputation of the sellers. In the final group, institutional infrastructure, legal functionalities such as resolution of disputes, intellectual property protection, monitoring of transactions and providing market information about competition of government regulations take place.

E-marketplaces provide a very important channel for sellers because they have high traffic which means high amount of potential customers. Most of the customers prefer accomplishing their buying process from a marketplace because of trust and other services. They search products directly from the e-marketplace which means acquiring new customer and increased sales for the sellers

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[42]. In one of the recent surveys on marketplace users, Hyperwallet [20] stated that most of the e-marketplace users sell their product solely from e-marketplaces where more than 40% sell both from marketplaces and other e-commerce channels. The research also reveals that the most common e-marketplaces are Ebay, Amazon and Etsy. While the first two do not specify any particular product group, Etsy is only used for creative products. The most important factors affecting users selection of e-market places are number of buyers on the marketplace, shipping options, and fees.

E-marketplaces, with the above-mentioned functionalities, support companies in finding new customers and enable secure and safe transactions. However, companies still need to handle many e-marketplace-related backoffice issues. Besides, there are fixed and variable costs associated with taking place on an e-marketplace. As a result, operating on an e-marketplace provides a new channel for companies but requires additional efforts and costs. This leads companies to selection of e-market places to operate on. This selection problem can be modeled as a multi-attribute decision-making (MADM) problem since it contains various evaluation perspectives. MADM concentrates on problems with discrete decision spaces and predefined decision alternatives.

In the classical approach, MADM methods capture decision makers' evaluations, represent it by numerical numbers, and reach to a result after mathematical operations. Either decision makers may assign numerical values or they use linguistic terms, which are then converted to crisp numbers. However, in real-world applications, either case may cause loss of information. In the first case, decision makers may have difficulties in representing his/her evaluation via crisp number. In the second case, decision makers use a linguistic term for evaluation, but this time representing a linguistic term with a single number may not be adequate. In order to deal with such cases, hesitant fuzzy sets [44] provide a structured approach to represent decision makers' evaluations. Using Hesitant Fuzzy Sets (HFS) membership value of an item to a specific set can take more than one value. This property enables decision makers' hesitancy to be transmitted into the decision problem; thus, better results can be obtained.

Decision makers may hesitate among several linguistic terms, while they express their assessments. For instance, they may hesitate between "Essentially High Importance (EHI)" and "Weakly High Importance (WHI)" when making an assessment. In this case, they may express their assessment as "between EHI and WHI." Rodriguez et al. [37] introduced hesitant fuzzy linguistic term sets (HFLTS) for improving the elicitation of linguistic information in decision making and providing more flexibility to the assessment process. HFLTS have been applied to various decision-making problems by many researchers in the literature [5, 8, 9, 14, 16, 22, 23, 30, 47].

In this paper, a modified version of Hesitant Fuzzy Analytic Hierarchy Process [5, 35] used to model e-marketplace selection. The originality of this paper comes from using hesitant fuzzy linguistic term sets in e-marketplace selection problem for the first time. The subjectivity and vagueness in the evaluation of e-marketplace alternatives are incorporated into the analysis through hesitant fuzzy sets. Buckley's ordinary fuzzy AHP has been transform to hesitant fuzzy linguistic AHP since Buckley's fuzzy AHP is almost the unique method without any criticism in the literature. Besides, multiple experts can assign different membership degrees or compromise on a joint membership degree. This joint membership degree may be defined as an interval such as "between good and very good" or "at most very good" rather than a single linguistic term. The proposed method can process such interval linguistic terms.

The rest of the paper is as follows. Section 2 presents a brief literature review of innovative project selection studies. Section 3 introduces hesitant fuzzy sets. The steps of the methodology are given in Sect. 4. Section 5 summarizes the numerical application and the sensitivity analysis. In the last section, the results are discussed and suggestions on future studies are given.

2 Literature Review

Fuzzy multi-attribute decision-making techniques are widely used in electronic business domain. The focuses of these are mainly on evaluating website quality, assessing website usability, or monitoring customer satisfaction. In one of the recent studies on website evaluation, Tzeng et al. [46] investigated a model for evaluating enterprise websites. The authors show that using fuzzy integral model provides better results since it can handle cases where independence and additive is not supported. The authors propose an algorithm to determine the λ-value using the input data of fuzzy densities and the fuzzy integral based on λ-fuzzy measure to determine the overall evaluation. Cebi [4] focused on assessing the perceived design quality of websites. In the study, interactions among design characteristics is handled using the decision-making trial and evaluation laboratory method (DEMATEL), and generalized Choquet integral techniques incorporation with fuzzy logic. DEMATEL is used to determine the critical design characteristics and their dependencies on each other. Later, Choquet Integral is used to evaluate the perceived design quality of website designs. The author incorporates fuzzy logic in order to deal with ambiguity in the linguistic evaluations. Büyüközkan and Çifçi [3] studied the e-service quality concept and its key components by employing service quality measure (SERVQUAL). They use an integrated methodology integrating fuzzy AHP and fuzzy TOPSIS. Chou and Cheng [11] developed a hybrid approach integrating fuzzy analytic hierarchy process (ANP) and fuzzy VIKOR for evaluating website quality of some firms in Taiwan. The results of the application it is found that the most important criteria are: richness, understandability, assurance, relevance, and reliability. Hsu et al. [19] proposed a hybrid ANP which integrates fuzzy preference relations with ANP model to evaluate the criteria of e-service quality. With the proposed approach, e-service quality can be measured with uncertain information with a high consistency. Lin [27] integrated triangular fuzzy numbers with AHP method in order to prioritize website quality factors. To this end, the author first makes an extended literature review to develop a decision model with four criteria and 16 sub-criteria. Later, this model is applied to two different groups. Finally, the results are compared to show the differences and similarities between high and low experience groups. Kaya [21] focused on e-business website quality evaluation using a MADM approach. The author defines a decision model composed of four main and nine sub-criteria, and use integrated AHP-TOPSIS method using ordinary fuzzy numbers.

The second branch of studies focuses on customer satisfaction and tries to define and model factors affecting satisfaction using fuzzy multi-attribute approach. In one of these studies, Nilashi and Ibrahim [34] used TOPSIS and fuzzy logic for detecting the level of customer intentions to purchase against factors affecting the intention to purchase in B2C websites. The authors define technology, shopping and product characteristics as the main three factors affecting customer satisfaction in B2C environment. After defining an extended list of B2C website features, they first use TOPSIS method to identify the most important features. In the second part, they model customer's perceptions and intention to purchase level using fuzzy logic. Chiu et al. [10] evaluated some strategies to remove the gaps in customer satisfaction caused by interdependence and feedback problems. They propose a model integrating DEMATEL, ANP, and VIKOR to solve these problems. Shee and Wang [43] focused on web-based e-learning systems and try to weigh the factors effecting learners' satisfaction. The authors apply the methodology on college students using AHP method and find out that a learner interface is the most important criteria for the e-learners.

In recent studies, fuzzy multi-attribute approaches are used to define and assess the criteria which affect usability perception of customers. Pearson and Pearson [36] analyzed the five main criteria affect individual's assessment of a website's usability. Using a MCDM approach, the authors find that *ease of use* and *navigation* are the most important factors of website usability. The authors also show that personal properties like; gender, computer anxiety, innovativeness, and self-efficacy has a significant effect on these factors. Muhtaseb et al. [33] focused on identifying the factors that affect e-commerce website usability and their role in increasing the effectiveness of e-commerce websites. The authors also utilize multi-attribute analysis approach to rank usability attributes in websites based on their importance. The authors present a case study involving eight e-tourism websites and the results show that for each e-commerce website certain usability attributes are likely to be more crucial to the success of the e-commerce website than others.

Besides the main branches of topics, there are various fuzzy multi-attribute studies that focus on different topics of e-business. Denguir-Rekik et al. [12] developed a recommender system framework based on MADM. In the proposed approach, customers' satisfaction levels form different e-commerce companies and services are stored in a database. Based on multi-criteria evaluations, new users can compare the alternatives and select the best one for them. Herre-Viedma et al. [18] focused on quality of information in a website using fuzzy computing. The propose approach is based on user's perceptions, and fuzzy linguistic techniques are involved in the quality evaluation process.

In this paper, we use HFLTS in the proposed hesitant fuzzy linguistic AHP. Torra [44] introduced Hesitant Fuzzy Sets (HFSs) since determining the membership degree of an element to a fuzzy set is not an easy work. The difficulty comes from several possible membership values and you have to determine which one would be the right one. Hesitant fuzzy sets have been improved by many researchers in the literature.

Xia and Xu [51] developed a series of aggregation operators for hesitant fuzzy information. Xu and Xia [53] proposed a variety of distance measures for hesitant fuzzy sets and develop a number of hesitant ordered weighted distance measures and hesitant ordered weighted similarity measures. Chen et al. [7] introduced interval-valued hesitant preference relations to describe uncertain evaluation information in group decision-making processes. Zhang and Wei [54] developed an extended VIKOR (E-VIKOR) method and TOPSIS method to solve the MCDM problems with hesitant fuzzy set information Liao, and Xu [24] extended the classical VIKOR method to its hesitant fuzzy version and developed the hesitant normalized Manhattan Lp—metric, the hesitant fuzzy group utility measure, the hesitant fuzzy individual regret measure, and the hesitant fuzzy compromise measure.

Rodriguez et al. [37] introduced the concept of a hesitant fuzzy linguistic term set (HFLTS) to provide a linguistic and computational basis to increase the richness of linguistic elicitation based on context-free grammars by using comparative terms. These sets provide greater flexibility to elicit comparative linguistic expressions by using context-free grammars. Rodríguez et al. [39] proposed a new linguistic group decision model for expressing linguistic preferences based on hesitant fuzzy linguistic term sets and context-free grammars. Liao et al. [25] developed different types of distance and similarity measures for HFLTSs for discrete and continuous cases. Liao et al. [26] proposed several different correlation measures and correlation coefficients of HFLTSs. Xu et al. [52] developed a hesitant fuzzy linguistic ordered weighted distance (HFLOWD) operator and its main properties and different families. Rodriguez et al. [38] studied the necessity of HFSs and provided a discussion about current proposals including a guideline that should be followed by the proposals and some challenges of HFSs. Gou and Xu [17] redefine some more logical operational laws for linguistic terms, hesitant fuzzy linguistic elements and probabilistic linguistic term sets based on two equivalent transformation functions. Wang and Xu [48, 49] develop total orders of extended HFLTSs. A constructive approach is proposed to generate total orders by aggregation functions. Three distinct total orders are defined for potential applications. Wang and Xu [48, 49] discuss the consistency and the completing algorithms of incomplete linguistic preference relations by interacting with the experts. Their algorithm estimates all possible linguistic terms and represents them by the extended hesitant fuzzy linguistic terms sets. Chang [6] integrates the HFLTSs, and minimal variance-ordered weighted geometric averaging (OWGA) weights to affect flexible allocation of system reliability. Montserrat-Adell et al. [32] define distances between hesitant fuzzy linguistic descriptions. A centroid of the decision-making group is proposed for each distance. Montes et al. [31] implement an intelligent decision support system in the platform based on computing with words in order to help creating values of confidence, trust and safety among the members of the Senegalese Teranga Go! community. They applied a multi-expert multi-criteria decision-making model using hesitant fuzzy linguistic terms to represent the expert opinions. Esposito et al. [13] present a fuzzy technique to combine qualitative and quantitative specifications of trust scores aiming at periodically computing a new trust degree. They use both linguistic term sets and hierarchies.

3 Hesitant Fuzzy Sets

Definition 1 Let X be a fixed set, a hesitant fuzzy set (HFS) on X is in terms of a function that when applied to X returns a subset of [0, 1] [44]. Mathematical expression for HFS is as follows [51]:

$$E = \{\langle x, h_E(x)\rangle | x \in X\}, \tag{1}$$

where $h_E(x)$ is a set of some values in [0, 1], denoting the possible membership degrees of the element $x \in X$ to the set E.

Definition 2 (Rodríguez et al. [37]) A HFLTS is an ordered finite subset of consecutive linguistic terms of $S = \{s_0,\ldots,s_g\}$. For instance, let S be defined as $S = \{s_0$: nothing, s_1: very bad, s_2: bad, s_3: medium, s_4: good, s_5: very good, s_6: perfect$\}$ and υ be a linguistic variable,

$$H_s(\upsilon) = \{\text{medium, good, very good}\}$$

Liao et al. [26] define HFLTS mathematically as follows:

Let $x_i \in X (i = 1, 2, \ldots, N)$, be fixed and $S = \{s_t | t = -\tau, \ldots, -1, 0, 1, \ldots, \tau\}$ be a linguistic term set. A HFLTS on X, H_S, is in mathematical form of $H_S = \{ < x_i, h_S(x_i) > | x_i \in X\}$, where $h_s(x_i)$ is a set of some values in S and can be expressed as $h_s(x_i) = \left\{s_{\phi_l}(x_i) | s_{\phi_l}(x_i) \in S, l = 1, \ldots, L\right\}$ with L being the number of linguistic terms in $h_s(x_i)$ where $h_s(x_i)$ denotes the possible degree of the linguistic variable x_i to S.

Definition 3 An ordered weighted averaging (OWA) operator of dimension n is a mapping OWA: $R^n \to R$, so that [44]

$$\mathrm{OWA}(a_1, a_2, \ldots, a_n) = \sum_{j=1}^{n} w_j b_j \tag{2}$$

where b_j is the jth largest of the aggregated arguments $a_1, a_2, \ldots, a_n$, and $W = (w_1, w_2, \ldots, w_n)^{\mathrm{T}}$ is the weighting vector so that $w_i \in [0, 1], i = 1, 2, \ldots, n$ and $\sum_{i=1}^{n} w_i = 1$.

Let s_i and s_j be linguistic terms and the evaluation is "between s_i and s_j" where $s_0 \leq s_i < s_j \leq s_{10}$. The parameters a, b, c and d of the trapezoidal fuzzy membership function (a, b, c, d) are computed as [28]:

$$a = \min\left\{a_l^i, a_m^i, a_l^{i+1}, \ldots, a_m^j, a_u^j\right\} = a_l^i \tag{3}$$

$$d = \max\left\{a_l^i, a_m^i, a_l^{i+1}, \ldots, a_m^j, a_u^j\right\} = a_u^j \tag{4}$$

$$b = \begin{cases} a_m^i, & \text{if } i+1 = j \\ \mathrm{OWA}_{w^2}\left(a_m^i, \ldots, a_m^{\frac{i+j}{2}}\right), & \text{if } i+j \text{ is even} \\ \mathrm{OWA}_{w^2}\left(a_m^i, \ldots, a_m^{\frac{i+j-1}{2}}\right), & \text{if } i+j \text{ is odd} \end{cases} \tag{5}$$

$$c = \begin{cases} a_m^{i+1}, & \text{if } i+1 = j \\ \mathrm{OWA}_{w^1}\left(a_m^j, a_m^{j-1}, \ldots, a_m^{\frac{i+j}{2}}\right), & \text{if } i+j \text{ is even} \\ \mathrm{OWA}_{w^1}\left(a_m^j, a_m^{j-1}, \ldots, a_m^{\frac{i+j+1}{2}}\right), & \text{if } i+j \text{ is odd} \end{cases} \tag{6}$$

where a_l^i and a_u^j are the minimum and maximum values when the parameters of the considered trapezoidal fuzzy numbers are ranked, respectively.

Table 1 Linguistic scale for hesitant fuzzy linguistic AHP

	Linguistic term	Abb.	Triangular fuzzy number
s_{10}	Absolutely high importance	(AHI)	(7, 9, 9)
s_9	Very high importance	(VHI)	(5, 7, 9)
s_8	Essentially high importance	(ESHI)	(3, 5, 7)
s_7	Weakly high importance	(WHI)	(1, 3, 5)
s_6	Equally high importance	(EHI)	(1, 1, 3)
s_5	Exactly equal	(EE)	(1, 1, 1)
s_4	Equally low importance	(ELI)	(0.33, 1, 1)
s_3	Weakly low importance	(WLI)	(0.2, 0.33, 1)
s_2	Essentially low importance	(ESLI)	(0.14, 0.2, 0.33)
s_1	Very low importance	(VLI)	(0.11, 0.14, 0.2)
s_0	Absolutely low importance	(ALI)	(0.11, 0.11, 0.14)

The weight vector of OWA operator is obtained by Eq. (7) [15] as follows:

$$w_1^1 = \alpha_2, w_2^1 = \alpha_2(1-\alpha_2), \ldots, w_n^1 = \alpha_2(1-\alpha_2)^{n-2} \tag{7}$$

The second kind of weights $W^2 = (w_1^2, w_2^2, \ldots, w_n^2)$ is defined as:

$$w_1^2 = \alpha_1^{n-1}, w_2^2 = (1-\alpha_1)\alpha_1^{n-2}, \ldots, w_n^2 = 1-\alpha_1, \tag{8}$$

where $\alpha_1 = \frac{g-(j-i)}{g-1}$ and $\alpha_2 = \frac{(j-i)-1}{g-1}$, g is the number of terms in the evaluation scale, j is the rank of highest evaluation and i is the rank of lowest evaluation value.OWA operator transforms $(\tilde{P})$ into the numerical pairwise comparison matrix $(\tilde{C})$.

$$\tilde{C} = \begin{vmatrix} (1,1,1,1) & \tilde{c}_{12} & \ldots & \tilde{c}_{1n} \\ \tilde{c}_{21} & (1,1,1,1) & \ldots & \tilde{c}_{2n} \\ \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ \tilde{c}_{n1} & \tilde{c}_{n2} & \ldots & (1,1,1,1) \end{vmatrix} \tag{9}$$

where $\tilde{c}_{ij} = (c_{ijl}, c_{ijm1}, c_{ijm2}, c_{iju})$.The reciprocal of $\tilde{c}_{ij}$ is obtained as follows:

$$\tilde{c}_{ji} = \left(\frac{1}{c_{iju}}, \frac{1}{c_{ijm2}}, \frac{1}{c_{ijm1}}, \frac{1}{c_{ijl}}\right) \tag{10}$$

4 Hesitant Fuzzy Linguistic AHP Method

The hesitant fuzzy linguistic AHP model used in this paper is a modification of the models in Oztaysi et al. [35] and Cevik et al. [5]. In the first step, experts evaluate attributes, sub-attributes and alternatives using HFLTS and the context-free grammar "between" and "is." The evaluations are given such as "between weakly high importance and very high importance," or "is very low important." In these evaluations, the linguistic scale given in Table 1 has been utilized. For every level in the hierarchy, pairwise linguistic evaluations are conducted.

Step 1 Define the pairwise comparison matrix $\tilde{P}$ as follows;

$$\tilde{P} = \begin{vmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \ldots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \ldots & \tilde{a}_{2n} \\ \vdots & \vdots & \ldots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \ldots & \tilde{a}_{nn} \end{vmatrix} \tag{11}$$

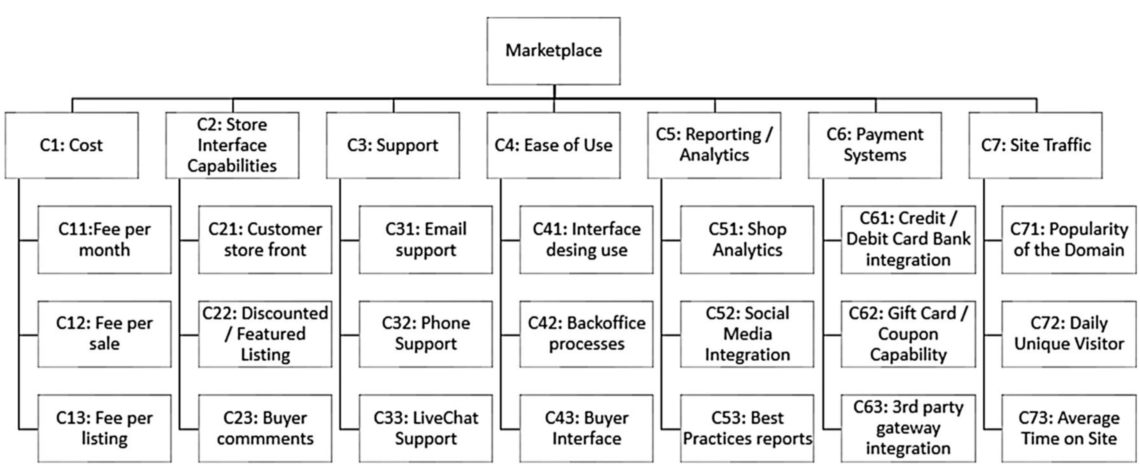

Fig. 1 Criteria hierarchy for e-marketplace prioritization

Table 2 Pairwise comparison of main criteria using HFLTS

Criteria	Cost	Store interface capabilities	Support	Ease of use	Reporting/analytics	Payment systems	Site traffic
Cost	EE	Between EHI and WHI	EE	ESHI	Between WHI and ESHI	EHI	Between ELI and EE
Store interface capabilities		EE	EE	EHI	Between EE and EHI	ELI	ELI
Support			EE	EE	Between ELI and EE	WLI	Between ESLI and WLI
Ease of use				EE	Between ELI and EE	ELI	WLI
Reporting/analytics					EE	Between WLI and ELI	WLI
Payment systems						EE	ELI
Site traffic							EE

Table 3 Aggregated HFLTS scores

	Cost	Store interface capabilities	Support	Ease of use	Reporting/analytics	Payment systems	Site traffic
Cost	(1, 1, 1, 1)	(1, 1, 3, 5)	(1, 1, 1, 1)	(3, 5, 5, 7)	(1, 3, 5, 7)	(1, 1, 1, 3)	(0.33, 1, 1, 1)
Store interface capabilities	(0.2, 0.33, 1, 1)	(1, 1, 1, 1)	(1, 1, 1, 1)	(1, 1, 1, 3)	(1, 1, 1, 3)	(0.33, 1, 1, 1)	(0.33, 1, 1, 1)
Support	(1, 1, 1, 1)	(1, 1, 1, 1)	(1, 1, 1, 1)	(1, 1, 1, 1)	(0.33, 1, 1, 1)	(0.2, 0.33, 0.33, 1)	(0.14, 0.2, 0.33, 1)
Ease of use	(0.14, 0.2, 0.2, 0.33)	(0.33, 1, 1, 1)	(1, 1, 1, 1)	(1, 1, 1, 1)	(0.33, 1, 1, 1)	(0.33, 1, 1, 1)	(0.2, 0.33, 0.33, 1)
Reporting/analytics	(0.14, 0.2, 0.33, 1)	(0.33, 1, 1, 1)	(1, 1, 1, 3)	(1, 1, 1, 3)	(1, 1, 1, 1)	(0.2, 0.33, 1, 1)	(0.2, 0.33, 0.33, 1)
Payment systems	(0.33, 1, 1, 1)	(0.33, 1, 1, 3)	(1, 3, 3, 5)	(1, 1, 1, 3)	(1, 1, 3, 5)	(1, 1, 1, 1)	(0.33, 1, 1, 1)
Site traffic	(1, 1, 1, 3)	(1, 1, 1, 3)	(1, 3, 5, 7)	(1, 3, 3, 5)	(1, 3, 3, 5)	(1, 1, 1, 3)	(1, 1, 1, 1)

Consistency ratio = 8%

Table 4 Calculation of defuzzified weights of the main attributes

	Geometric mean	Normalized weights	Crisp weights
Cost	(1, 1.472, 1.853, 2.567)	(0.079, 0.182, 0.263, 0.57)	0.211
Store interface capabilities	(0.581, 0.855, 1, 1.369)	(0.046, 0.106, 0.142, 0.304)	0.115
Support	(0.514, 0.679, 0.731, 1)	(0.041, 0.084, 0.104, 0.222)	0.087
Ease of use	(0.376, 0.679, 0.679, 0.855)	(0.03, 0.084, 0.097, 0.19)	0.077
Reporting/analytics	(0.409, 0.581, 0.731, 1.369)	(0.032, 0.072, 0.104, 0.304)	0.099
Payment systems	(0.624, 1.17, 1.369, 2.168)	(0.049, 0.145, 0.194, 0.481)	0.167
Site traffic	(1, 1.601, 1.723, 3.349)	(0.079, 0.198, 0.245, 0.744)	0.244

Table 5 Pairwise comparison of sub-criteria with respect to C1

w.r.t. C1	Fee per month	Fee per sale	Fee per listing	Normalized local weights	Crisp weights
Fee per month	EE	Between EHI and WHI	EHI	(0.193, 0.257, 0.581, 1)	0.412
Fee per sale		EE	Between WLI and ELI	(0.066, 0.124, 0.403, 0.491)	0.22
Fee per listing			EE	(0.134, 0.257, 0.581, 0.84)	0.368

Consistency ratio: 0.15%

Table 6 Pairwise comparison of sub-criteria with respect to C6

w.r.t. C6	Credit/debit card bank integration	Gift card/coupon capability	3rd party gateway integration	Normalized local weights	Crisp weights
Credit/debit card bank integration	EE	EHI	Between EHI and WHI	(0.204, 0.291, 0.535, 1)	0.436
Gift card/coupon capability		EE	Between EE and EHI	(0.141, 0.291, 0.371, 0.687)	0.32
3rd party gateway integration			EE	(0.083, 0.201, 0.371, 0.476)	0.243

Consistency ratio: 1%

Table 7 Pairwise comparison of the alternatives with respect to C11

w.r.t. C11	Alt1	Alt2	Alt3	Alt4	Alt5	Normalized local weights	Crisp weights
Alt1	EE	Between WLI and ELI	Between ESLI and WLI	ELI	Between ELI and EE	(0.035, 0.088, 0.183, 0.342)	0.121
Alt2		EE	ELI	EHI	Between EHI and WHI	(0.086, 0.172, 0.316, 0.674)	0.233
Alt3			EE	Between EHI and WHI	WHI	(0.114, 0.227, 0.473, 1)	0.338
Alt4				EE	EHI	(0.058, 0.131, 0.24, 0.451)	0.164
Alt5					EE	(0.039, 0.099, 0.183, 0.451)	0.144

Consistency ratio: 1%

Table 8 Pairwise comparison of the alternatives with respect to C73

w.r.t. C73	Alt1	Alt2	Alt3	Alt4	Alt5	Normalized local weights	Crisp weights
Alt1	EE	Between WLI and ELI	ELI	Between ELI and EE	EE	(0.047, 0.137, 0.254, 0.355)	0.151
Alt2		EE	EHI	Between WHI and ESHI	Between ESHI and VSHI	(0.121, 0.237, 0.5, 1)	0.354
Alt3			EE	Between EHI and WHI	WHI	(0.092, 0.18, 0.334, 0.699)	0.249
Alt4				EE	Between EHI and WHI	(0.05, 0.092, 0.193, 0.467)	0.153
Alt5					EE	(0.031, 0.064, 0.129, 0.27)	0.094

Consistency ratio: 6%

Table 9 Global weights of the sub-criteria

Sub-criteria	Global weights	Defuzzified weights	Normalized weights
Fee per month	(0.015, 0.047, 0.153, 0.57)	0.164	0.091
Fee per sale	(0.003, 0.023, 0.106, 0.28)	0.090	0.050
Fee per listing	(0.005, 0.047, 0.153, 0.479)	0.147	0.081
Customer store front	(0.007, 0.035, 0.047, 0.202)	0.062	0.034
Discounted/featured listing	(0.005, 0.035, 0.047, 0.14)	0.052	0.029
Buyer comments	(0.01, 0.035, 0.047, 0.291)	0.078	0.043
Email support	(0.005, 0.019, 0.023, 0.155)	0.040	0.022
Phone support	(0.004, 0.027, 0.033, 0.107)	0.039	0.021
Live chat support	(0.008, 0.039, 0.048, 0.222)	0.067	0.037
Interface design use	(0.004, 0.022, 0.056, 0.16)	0.053	0.029
Backoffice processes	(0.002, 0.01, 0.039, 0.093)	0.032	0.018
Buyer interface	(0.006, 0.022, 0.056, 0.19)	0.059	0.032
Shop analytics	(0.003, 0.013, 0.037, 0.22)	0.054	0.030
Social media integration	(0.006, 0.028, 0.076, 0.304)	0.086	0.048
Best practices reports	(0.002, 0.013, 0.025, 0.153)	0.039	0.021
Credit/debit card bank integration	(0.01, 0.042, 0.104, 0.481)	0.130	0.072
Gift card/coupon capability	(0.007, 0.042, 0.072, 0.33)	0.094	0.052
3rd party gateway integration	(0.004, 0.029, 0.072, 0.229)	0.073	0.040
Popularity of the domain	(0.014, 0.069, 0.222, 0.744)	0.223	0.123
Daily unique visitor	(0.005, 0.028, 0.062, 0.382)	0.095	0.052
Average time on site	(0.008, 0.033, 0.09, 0.551)	0.134	0.074

where $(\tilde{a}_{ij})$ represents the HFLTS evaluation on comparison of ith element to jth element.

Step 2 Transform the HFLTS evaluations into trapezoidal fuzzy numbers by using OWA operator given in Eqs. (2)–(8) and the scale given in Table 1 [28]. Thus, the numerical pairwise comparison matrix $(\tilde{C})$ given in Eq. (9) is obtained where $\tilde{c}_{ij} = (c_{ijl}, c_{ijm1}, c_{ijm2}, c_{iju})$.

Step 3 Measure the consistency ratio of the transformed comparison matrix. For this purpose, we first defuzzify the pairwise comparison matrix and then the consistency ratio is calculated based on Saaty's classical consistency measurement [41].

Step 4 Calculate the geometric mean for each row $(\tilde{r}_i)$ in $\tilde{C}$ as follows [1]:

$$\tilde{r}_i = (\tilde{c}_{i1} \otimes \tilde{c}_{i2} \ldots \otimes \tilde{c}_{in})^{1/n} \tag{12}$$

and

$$\tilde{r}_i = \left(\sqrt[n]{\prod_{j=1}^{n} c_{ijl}}, \sqrt[n]{\prod_{j=1}^{n} c_{ijm1}}, \sqrt[n]{\prod_{j=1}^{n} c_{ijm2}}, \sqrt[n]{\prod_{j=1}^{n} c_{iju}} \right) \tag{13}$$

which can be represented by $\tilde{r}_i = (r_{il}, r_{im1}, r_{im2}, r_{iu})$

Step 5 Calculate the fuzzy weight $(\tilde{w}_i)$ of each main-attribute, sub-attribute and alternative using $(\tilde{r}_i)$ values as follows [1]:

$$\tilde{w}_i = r_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \ldots \oplus \tilde{r}_n)^{-1} \tag{14}$$

and

$$\tilde{w}_i = \left(\frac{r_{il}}{\sum_{i=1}^{n} r_{iu}}, \frac{r_{im1}}{\sum_{i=1}^{n} r_{im2}}, \frac{r_{im2}}{\sum_{i=1}^{n} r_{im1}}, \frac{r_{iu}}{\sum_{i=1}^{n} r_{il}} \right) \tag{15}$$

Step 6 Obtain the fuzzy performance score of each alternative, $\tilde{S}_j = (S_{jl}, S_{jm1}, S_{jm2}, S_{ju})$, by Eq. (16) [29].

$$\tilde{S}_j = \sum_{i=1}^{n} \tilde{w}_i \otimes \tilde{s}_{ij}, \forall i. \tag{16}$$

where $\tilde{w}_i$ is the weight of the attribute i, and $\tilde{s}_{ij}$ is the performance score of alternative j with respect to attribute i. To obtain $\tilde{s}_{ij}$, Steps 1–5 are repeated for pairwise comparison of alternatives with respect to each criterion.

Step 7 Defuzzify the importance ranking of the alternatives as follows [40]:

$$D = \frac{S_{jl} + 2S_{jm1} + 2S_{jm2} + S_{ju}}{6} \tag{17}$$

The alternatives are ranked according to these values.

Table 10 Weights of alternatives with respect to sub-criteria

Sub-criteria	Global fuzzy weights	Sub-criteria	Global fuzzy weights
Fee per month		*Fee per listing*	
Alt1	(0.001, 0.004, 0.028, 0.195)	Alt1	(0, 0.004, 0.025, 0.152)
Alt2	(0.001, 0.008, 0.048, 0.384)	Alt2	(0.001, 0.015, 0.074, 0.479)
Alt3	(0.002, 0.011, 0.072, 0.57)	Alt3	(0, 0.005, 0.033, 0.227)
Alt4	(0.001, 0.006, 0.037, 0.257)	Alt4	(0, 0.007, 0.033, 0.247)
Alt5	(0.001, 0.005, 0.028, 0.257)	Alt5	(0, 0.004, 0.044, 0.298)
Fee per sale		*Customer store front*	
Alt1	(0, 0.004, 0.043, 0.25)	Alt1	(0.001, 0.007, 0.012, 0.158)
Alt2	(0, 0.001, 0.016, 0.078)	Alt2	(0.001, 0.007, 0.015, 0.137)
Alt3	(0, 0.002, 0.022, 0.103)	Alt3	(0.001, 0.007, 0.015, 0.104)
Alt4	(0, 0.003, 0.028, 0.154)	Alt4	(0, 0.004, 0.012, 0.069)
Alt5	(0, 0.004, 0.074, 0.28)	Alt5	(0, 0.003, 0.009, 0.069)
3rd party gateway integration		*Daily unique visitor*	
Alt1	(0, 0.007, 0.032, 0.229)	Alt1	(0, 0.007, 0.02, 0.292)
Alt2	(0, 0.007, 0.032, 0.19)	Alt2	(0, 0.007, 0.02, 0.222)
Alt3	(0, 0.002, 0.014, 0.085)	Alt3	(0.001, 0.007, 0.018, 0.354)
Alt4	(0, 0.003, 0.018, 0.127)	Alt4	(0, 0.002, 0.006, 0.137)
Alt5	(0, 0.001, 0.011, 0.085)	Alt5	(0, 0.002, 0.008, 0.137)
Popularity of the domain		*Average time on site*	
Alt1	(0.001, 0.009, 0.076, 0.403)	Alt1	(0, 0.005, 0.023, 0.196)
Alt2	(0.001, 0.012, 0.076, 0.531)	Alt2	(0.001, 0.008, 0.045, 0.551)
Alt3	(0.002, 0.016, 0.1, 0.744)	Alt3	(0.001, 0.006, 0.03, 0.385)
Alt4	(0, 0.005, 0.044, 0.27)	Alt4	(0, 0.003, 0.017, 0.258)
Alt5	(0, 0.004, 0.025, 0.27)	Alt5	(0, 0.002, 0.012, 0.149)

5 A Case Study

In this section, an application of hesitant fuzzy linguistic AHP is presented on a real-world case study. The case study is from a textile manufacturing company, which produces and sells textile products with its own brand. The company currently operates its own e-commerce website and on the other hand plans to operate on B2C e-marketplaces in order to expand its market. Since each B2C e-marketplace has different processes, requirements and associated costs, the company wants to prioritize the alternative e-marketplaces. The alternative e-marketplaces are all international marketplaces, but due to the legal rights of the firms, their names are not given in the text. We define the alternatives as Alt1, Alt2, …, Alt5.

5.1 Decision Hierarchy

The criteria used for B2C e-marketplace prioritization are determined as a result of a comprehensive literature review, and then modifications are made based on the domain experts' comments. As a result, a decision hierarchy with seven criteria and 21 sub-criteria is proposed as shown in Fig. 1 [2, 4, 21, 43].

There are seven main criteria in the proposed decision hierarchy. *Cost* (C1) is the first main criterion, as the name implies, it focuses on the cost of operating on the marketplace. Monthly fee, transaction based fee and fee per listing are the sub-criteria defined under this main criterion. The second main criterion is *Store interface capabilities* (C2) which focuses on functionality of the buyers' interface. The third criterion, *Support* (C3), represents the availability and quality of alternative technical support channels provided to the sellers. *Ease of use* (C4) is the next criterion, which represents the usability of interfaces. *Reporting and Analytics* (C5) focuses on business intelligence applications provided by the e-marketplace that the sellers can use. Payment channels and timing is a very important issue and represented under *Payment systems* (C6). Popularity of the marketplace is also very important since it is the main reason for increased sales. This issue is handled under seventh criterion *Traffic* (C7) and it contains

Table 11 Defuzzified weights of the alternatives

Sub-criteria	Alt1	Alt2	Alt3	Alt4	Alt5
Fee per month	0.043	0.083	0.123	0.057	0.054
Fee per sale	0.057	0.019	0.025	0.036	0.072
Fee per listing	0.035	0.11	0.051	0.054	0.066
Customer store front	0.033	0.03	0.025	0.017	0.016
Discounted/featured listing	0.025	0.014	0.018	0.013	0.018
Buyer comments	0.049	0.044	0.032	0.026	0.026
Email support	0.022	0.031	0.011	0.015	0.011
Phone support	0.025	0.018	0.009	0.015	0.009
Live chat support	0.049	0.041	0.023	0.017	0.009
Interface design use	0.038	0.017	0.022	0.02	0.015
Backoffice processes	0.019	0.019	0.013	0.008	0.008
Buyer interface	0.028	0.042	0.023	0.015	0.02
Shop analytics	0.037	0.022	0.017	0.014	0.032
Social media integration	0.035	0.043	0.024	0.054	0.03
Best practices reports	0.013	0.016	0.01	0.027	0.02
Credit/debit card bank integration	0.051	0.051	0.041	0.034	0.034
Gift card/coupon capability	0.071	0.026	0.034	0.057	0.024
3rd party gateway integration	0.051	0.045	0.02	0.028	0.018
Popularity of the domain	0.096	0.118	0.163	0.061	0.055
Daily unique visitor	0.058	0.046	0.067	0.025	0.026
Average time on site	0.042	0.11	0.076	0.05	0.029
Total	0.226	0.243	0.213	0.166	0.152

Table 12 Comparison with ordinary fuzzy AHP

	Alt1	Alt2	Alt3	Alt4	Alt5
Buckley's AHP (pessimistic)	0.205	0.245	0.221	0.177	0.152
Buckley's AHP (optimistic)	0.257	0.256	0.217	0.153	0.117
Buckley's AHP (aggregated)	0.23	0.251	0.22	0.164	0.135
Proposed method	0.226	0.243	0.213	0.166	0.152

sub-criteria, site popularity, and number of unique visitors, and average time on site.

5.2 Numerical Application

A team of three experts assigned the compromised importance assessments for the main criteria. The experts having the sufficient experience on e-marketplaces were selected from Business Administration Department of the university. The evaluation data have been produced by these experts. Table 2 presents these assessments using HFLTS given in Table 1.

Using the OWA operations in Eqs. (2)–(8), HFLTSs are converted to trapezoidal fuzzy numbers which are given in Table 3. The consistency ratio of the matrix in Table 3 is measured and found to be 0.08.

The defuzzified weights of the main criteria are given in Table 4. Geometric means of the trapezoidal fuzzy numbers in Table 3 are calculated by using Eq. (12). Normalized weights are obtained based on Eq. (14). Defuzzified weights are calculated by using Eq. (17).

There are totally seven pairwise comparison matrices of sub-criteria with respect to the main criteria. Because of the space constraints, we only give the first pairwise comparison matrix (Table 5) and the last pairwise comparison matrix (Table 6) for the main criteria C1 and C6, respectively. The consistency ratios of the matrices in Tables 5 and 6 are measured and found to be 0.015 and 0.01, respectively.

There are totally 21 pairwise comparison matrices of alternatives with respect to the sub-criteria. Because of the space constraints, we only give the first matrix for C11 (Table 7) and the last one for C73 (Table 8). The consistency ratios of the matrices in Tables 7 and 8 are measured and found to be 0.01 and 0.01, respectively.

Table 9 presents the global weights of the sub-criteria.

Table 10 gives the weights of alternatives with respect to sub-criteria. Because of space constraints, we only present the results of eight sub-criteria.

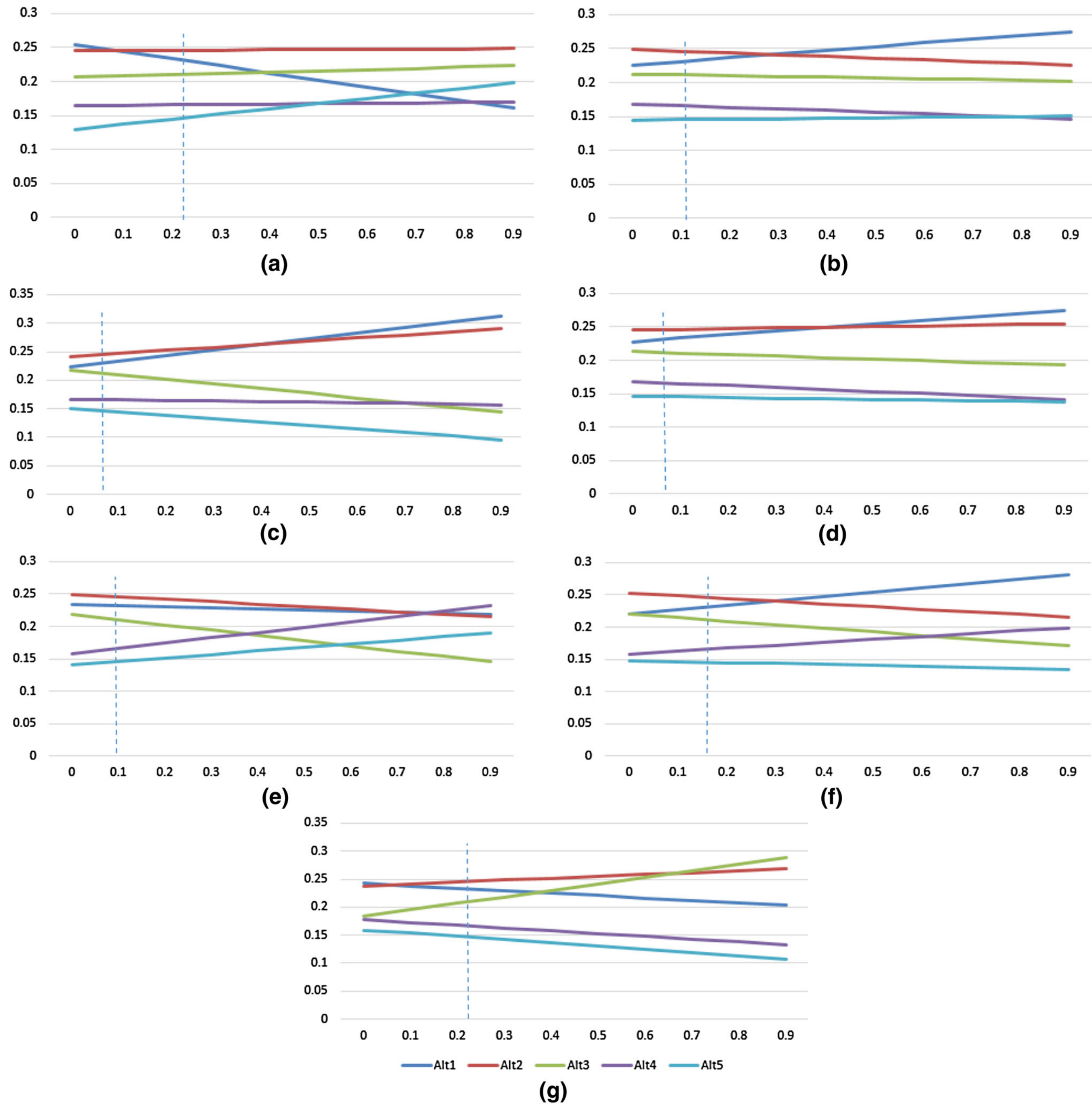

Fig. 2 Sensitivity analysis

Table 11 presents the defuzzified weights of alternatives with respect to sub-criteria.

Based on the total scores of the alternatives, the best B2C e-marketplace is Alt2. In the next section, the robustness of the obtained ranking will be investigated.

6 Comparative and Sensitivity Analyses

We compared the proposed method with the Buckley's ordinary fuzzy AHP method. For comparison purposes, the interval linguistic evaluations such as between high importance and very high importance have been treated in three discrete points: lower value (pessimistic), middle value (aggregated), and upper value (optimistic). The results based on these three points have been obtained and presented in the text in Tabular form. The obtained prioritization results by Buckley's ordinary fuzzy AHP method are shown in Table 12:

The rankings of alternatives are slightly different from one method to the other. The best alternative is Alternative 2 with respect to the pessimistic values, while the best alternative is Alternative 1 with respect to optimistic values. The best alternative is Alternative 2 with respect to Buckley's aggregated values. The proposed method suggests Alternative 2 as the best alternative. We can say that Alternative 2 is superior to the others at most of the time.

In the following, a sensitivity analysis is realized to see the robustness of the given decisions by the proposed method and the decision model. One at-a-time sensitivity analysis is applied to the main criteria to see the effects of possible changes in their weights on the final ranking of the alternatives. Figures 2a–g illustrate the effects of possible changes in the weights on main criteria, and the current weights of the criteria are given with dashed line. Figure 2a shows the sensitivity analysis for *Cost* (C1) criterion. Alternative 2 is always selected for cases where the importance of Cost is over 0.1. Figure 2b shows the sensitivity analysis for *Store Interface Capabilities* (C2) criterion. For the weight values less than 0.3, Alt2 is selected as the best alternative, for other cases, Alt1 is the best alternative. Figure 2c shows the sensitivity analysis for *Support* (C3), Alt2 is the best alternative for values less than 0.4, for other cases, Alt1 becomes the best alternative. The case is very similar for *Ease of use* (C4) as shown in Fig. 2d. The sensitivity analysis for Reporting/Analytics (C5) is given in Fig. 2e, Alt2 is the best alternative until the weight of the criterion is 0.8, for higher weight values, Alt 4 becomes the best alternative. The sensitivity analysis of *Payment Systems* (C6) is shown in Fig. 2f for weight values higher than 0.3 Alt 4 is the best alternative, for other values the best alternative is Alt 2. Figure 2g shows the sensitivity analysis for *Site Traffic* (C7) criterion. For weight values lower than 0.1 Alt1 is the best alternative, for values between 0.1 and 0.65 Alt2 is the best alternative and for higher values, Alt3 is the best alternative. The analysis shows that for each criterion, slight changes in weights do not change the best alternative; this proves that a robust decision is given.

7 Conclusion

There are three types of e-marketplaces: Customer to customer (C2C), Business to Business (B2B), and Business to Customer (B2C). We developed a hesitant fuzzy multi-attribute model for the comparison of B2C marketplace alternatives. The developed model is based on hesitant fuzzy linguistic AHP method. For an efficient selection, we considered 21 sub-criteria under 7 main criteria, which were determined after a comprehensive search in the databases. The e-marketplaces of 5 international B2C firms have been compared based on these main and sub-criteria. The sensitivity analysis showed that the obtained rankings were robust to the changes in the criteria weights.

For further research, we suggest a similar model to be developed using other extensions of fuzzy sets such as intuitionistic fuzzy sets, type-2 fuzzy sets, neutrosophic sets, or Pythagorean fuzzy sets. Alternatively, the MADM method may be changed to another method such as hesitant fuzzy TOPSIS, intuitionistic fuzzy ELECTRE, or an integrated method of these.

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