AIMS Environmental Science
AIMS Environmental Science, 13(1): 1–22.
DOI: 10.3934/environsci.2026001
Received: 31 July 2025
Revised: 10 December 2025
Accepted: 07 January 2026
Published: 16 January 2026

http://www.aimspress.com/journal/environmental

Research article

An integrated MCDM approach for B2C e-marketplace selection in the healthy food sector

Emre Çakmak[1], Tutku Eker İşçioğlu[2], Ezgi İpek[2] and Erfan Babaee Tirkolaee[3,*]

[1] Department of Industrial Engineering, Istinye University, Istanbul 34396, Türkiye
[2] Faculty of Economics and Administrative Sciences, Piri Reis University, Istanbul, Türkiye
[3] Department of Industrial Engineering, Istinye University, Istanbul, Türkiye

* **Correspondence:** Email: erfan.babaee@istinye.edu.tr.

Abstract: Stochastic modeling and data analysis, which address uncertainty and complexity in business and industry, are important tools for optimizing decision-making processes. When it comes to providing access to healthy food, the importance of decision-making becomes even more prominent. In this work, the aim was to determine the criteria that healthy food businesses consider when choosing business-to-consumer (B2C) e-marketplaces and to evaluate the performance of alternative platforms. Nine main criteria were determined through a literature review and interviews with ten decision-makers (DMs), as sellers. To overcome the limitations of traditional fuzzy sets in handling uncertainty and inconsistent information, a hybrid decision-making method integrating interval-valued neutrosophic sets (IVNSs) with the stepwise weight assessment ratio analysis (SWARA) and evaluation based on distance from average solution (EDAS) methods was applied. Unlike existing approaches, this methodology better addresses expert uncertainty and inconsistency by simultaneously handling membership in truthiness, uncertainty, and falsity within an interval. Interval-valued neutrosophic (IVN)-SWARA was used to weight the selection criteria for e-marketplace platforms, and these weights were used to rank the platforms using IVN-EDAS. The findings show that integration capacity, site traffic density, and cost-effectiveness are the most important criteria in e-marketplace selection, while ease of membership and platform design usability were the least important. Theoretically, this research fills a gap in the literature by addressing B2C e-marketplace selection from the seller's perspective and better handles inconsistencies compared to standard fuzzy sets using IVN fuzzy sets. In addition, the proposed approach offers special solutions for healthy food businesses and sheds light on advanced research for other sectors and regions.

Keywords: B2C; e-marketplace; healthy food; MCDM; IVN-SWARA; IVN-EDAS

1. Introduction

E-commerce is a digitalized version of commerce, offering new opportunities for businesses, and is of strategic importance in today's economy. E-commerce has been growing rapidly since the invention of the Internet. More than five billion people now use the internet, and global retail e-commerce sales are expected to surpass 4.3 trillion dollars by 2025 [1].

While e-commerce has been growing and is expected to revolutionize economies, e-marketplaces play an important role in this transformation. Transactions such as information sharing, purchasing, and selling are carried out between various sellers and buyers through these digital platforms. Online marketplaces have represented the biggest portion of global online purchases since 2024 [1], and online marketplaces, such as Alibaba, eBay, or JD.com, made up nearly 30% of online shopping orders worldwide [2]. These electronic environments, which are similar to the functions of physical marketplaces, provide higher efficiency with up-to-date information, support services, and ease of transaction provided by the digital infrastructure [3]. Businesses, customers, and governments can be the participants of e-marketplace transactions, and accordingly, nine e-marketplace types (i.e., business-to-business (B2B), business-to-consumer (B2C), business-to-government (B2G), consumer-to-business (C2B), consumer-to-government (C2G), consumer-to-consumer (C2C), government-to-business (G2B), government-to-consumer (G2C), government-to-government (G2G)) can be generated (Naujoks, 2020). In this study, B2C e-marketplaces will be the focus.

Considering B2C e-marketplaces, studies in the literature mostly focus on which e-marketplaces consumers prefer and why. However, the number of studies investigating the reasons for businesses' preferences is quite low [4]. Especially when it comes to examining different businesses with respect to the different product categories they offer, academic research is observed to be even rarer. Therefore, this study focuses on the businesses offering healthy food, since selecting the right e-marketplace is crucial for them in terms of their visibility, cost, and functionality, as well as the user experience they offer to their consumers.

Healthy food consumption can be identified as one of the ways to achieve healthy living, eliminate obesity, and improve people's quality of life. Examples of products in the healthy food category include organic fruits and vegetables, plant-based milk, gluten-free products, high-protein snacks, and sugar-free alternatives to desserts, among others. Numerous attempts have been made to promote healthy food consumption. One such attempt is to make them more affordable, available, and easier to obtain, so that consumers can be more willing to buy and consume healthy food.

With so many retailers adopting e-commerce, there are also efforts to promote healthy food consumption through e-marketplaces. Various studies examined consumer behavior and motivations to develop an understanding of factors inclining them toward online grocery shopping, fresh food, and/or the purchase of healthy food (e.g., [5–9]). Accumulated research has found that consumers' shopping habits change toward the preference of e-commerce platforms, as they are more time-saving and convenient.

This research examines the key criteria to consider when choosing B2C e-marketplaces, considering the dynamics specific to the healthy food sector. Choosing the right e-marketplace is not just about listing products but also requires a detailed evaluation of a number of criteria, making it a critical factor for the success of businesses. This focus is especially necessary since such businesses must choose the right e-marketplace to ensure their products reach consumers safely and meet legal requirements. The wrong choice is not only limited to sales losses; it can damage brand reputation and negatively affect consumer trust in a sector that places great importance on health and well-being. It can be expected that these retailers will tend to prefer e-marketplaces that stand out in terms of high-quality customer service, positive user reviews, and reliability.

As mentioned earlier, studies examining the business side and their motivations for the selection of e-marketplaces appear to be comparatively low. To the knowledge of the authors, there has been no research focusing on the selection of e-marketplaces by healthy food businesses. In order to fill this research gap, this study aims to evaluate the e-marketplaces of the sellers doing business and to determine the criteria to be considered in the selection of these e-marketplaces for businesses selling healthy foods. Multi-criteria decision-making (MCDM) is used because it helps when there is no single, clear best choice for the decision-maker, meaning each alternative performs well on some criteria but falls short on others [10]. The nine main criteria are determined for the e-marketplace selection of businesses selling healthy foods through a literature review and interviews with ten DMs, who have been selling in e-marketplaces for a long time. Using the criteria obtained, seven e-marketplaces operating in Türkiye are evaluated. A hybrid fuzzy MCDM model is used, based on interval-valued neutrosophic stepwise weight assessment ratio analysis (IVN-SWARA) and interval-valued neutrosophic evaluation based on distance from average solution (IVN-EDAS) techniques. The reason for choosing this method is that it utilizes the benefits provided by interval-valued neutrosophic sets (IVNSs) in addressing uncertainties and inconsistencies of experts in decision-making processes [11]. On the other hand, the SWARA method is one of the most effective methods for determining the weights of the criteria, which attracts attention due to its simplicity, ease of application, and time saving [12,13]. EDAS technique, on the other hand, is preferred because it minimizes the effect of biased decisions and manages conflicting criteria effectively in decision environments involving uncertainty and imprecision [14,15].

The findings of this research reveal that the most remarkable criteria in the selection process are the integration capability of the site, site traffic density, and affordability of site costs. On the other hand, the least significant criteria are the usability of platform design, the ease of membership conditions, and the ability of sellers and consumers to interact with the site. Considering the preferred alternatives of B2C e-marketplaces, Trendyol, Hepsiburada, and Amazon are the most preferred, whereas Aliexpress, N11, and Shopier are the least preferred e-marketplaces of healthy food businesses.

2. Literature review

B2C e-marketplaces are platforms that help businesses sell their products, receive sales, conversion, and traffic data in real-time, and enable consumers to explore millions of products, access detailed feature descriptions and customer reviews, and engage in promotions, negotiations, ordering, and payment processes between sellers and buyers [16]. Various studies on e-marketplaces have been carried out using different methods to evaluate these platforms.

While previous research mostly focused on e-marketplace selection criteria from the customers' point of view, studies investigating the sellers' point of view are comparatively rare. Being one of the earliest in this research domain, Stockdale and Standing [17] content analyzed over 100 practitioner articles and identified three critical decision-related issues relating to the selection of an electronic marketplace: internal company factors, business drivers, and facilitators that contribute to the probable success of an e-marketplace. Using the hesitant fuzzy linguistic analytic hierarchy process (AHP) method to determine the importance levels of the criteria that businesses use when choosing among B2C marketplaces, Kahraman et al. [3] identified 7 main criteria, namely cost, support, store interface capabilities, reporting/analytics, payment systems, ease of use, and site traffic, and 21 sub-criteria. [18] addressed the sellers' alternatives in three e-marketplaces by combining VIKOR with the SMARTER method for MCDM, taking into account the number of products sold, product price, number of five-star reviews, seller rating, and location distance as selection criteria. With an aim to develop and validate a scale to measure sellers' experience with e-commerce platforms, Kumar, Sikdar, and Saha [19] identified six major dimensions: product listing, registration, ease of pick-up and delivery, pricing autonomy, credit of receivables, assistance, and vendor. Akman, Boyacı, and Kurnaz [20] determined 2 main and 8 sub-criteria that are significant in choosing the right e-marketplace and evaluated 8 alternative marketplaces (i.e., Trendyol, Bol, Flipkart, Allegro, Alibaba, Rakuten, Amazon, and Etsy) using neutrosophic fuzzy AHP and EDAS methods. The top three criteria for selecting an e-marketplace were identified as monthly fees charged by the platform, commission rates, and supported channel features. Among the eight evaluated e-marketplaces, Amazon ranked highest in preference. On the other hand, Çağlar [21] surveyed 392 sellers having stores in e-marketplaces and found out that the awareness level of the e-marketplace, commission rate, customer services, advertising activities, payment terms, operational costs, and analytical data are the most important factors while selecting an e-marketplace. Putri and Setiono [23] compared two B2C marketplaces with respect to price, product, place, promotion, people, physical facilities, and process from the sellers' point of view. A recent study undertaken by Bingöl and Karaarslan [4] examined the factors that are important in businesses' e-marketplace selection and the degree of importance of these factors. Four main factors (financial, strategic, organizational, and technological factors) and 15 sub-criteria were identified as a result of the evaluations made among the three most visited e-marketplaces using the AHP method. They emphasized that financial factors (especially commission rates) are the most critical factors for e-marketplace selection.

Table 1 shows the summary of academic research with respect to authors, method of analysis, research focus, publication year, and the number of criteria examined. Accordingly, while research has covered this topic mostly within the last three years, the majority of the research about e-marketplace selection has been published with a focus on consumers. On the other hand, studies investigating sellers' points of view while selecting e-marketplaces are fewer and were mostly examined with fewer criteria than the research focusing on consumers.

Table 1. Overview of academic studies on e-marketplaces.

Reference	Method of analysis	Focus	#Criteria
[17]	Content analysis	Sellers	4 main, 18 sub
[24]	Fuzzy Delphi	Sellers	3 main, 9 sub
[25]	AHP, ANP	Consumers	4 main, 22 sub
[26]	SWARA, WASPAS	Consumers	11 main
[3]	Hesitant fuzzy linguistic AHP	Sellers/experts	7 main, 21 sub
[27]	PCA	Consumers	3 main, 27 sub
[28]	AHP, TOPSIS	Consumers	7 main
[29]	WASPAS, SWARA	Consumers	8 main
[20]	NF AHP, EDAS	Sellers	2 main, 8 sub
[21]	Descriptive statistics	Sellers	7 main
[30]	AHP, MAIRCA	Consumers	5 main,23 sub
[31]	DANP, TOPSIS	Consumers	4 main,12 sub
[32]	MCDM, DEMATEL, EDAS	Consumers	10 main
[33]	Fuzzy TOPSIS	Consumers	6 main
[34]	PCA	Consumers	7 main
[4]	AHP	Sellers	4 main, 15 sub

AHP: Analytic hierarchy process; ANP: Analytic network process; DANP: DEMATEL-based analytic network process; DEMATEL: Decision-making trial and evaluation laboratory; EDAS: Evaluation based on distance from average solution; MAIRCA: Multi-attributive ideal-real comparative analysis; MCDM: Multi-criteria decision-making; NF AHP: Neutrosophic fuzzy analytic hierarchy process; PCA: Principal component analysis; SWARA: Stepwise weight assessment ratio analysis; TOPSIS: Technique for order preference by similarity to ideal solution; WASPAS: Weighted aggregated sum product assessment.

Academic studies concerning authors, methodologies, research focuses, and criteria are summarized in Table 1. Two significant gaps emerge from the studies in this table.

Looking at existing studies, many authors have focused on the consumer perspective. There are very few studies that look at the seller perspective. However, the AHP technique, one of the traditional successful methods, is the dominant methodology. Many publications have been made on methods developed with fuzzy sets using this technique. However, these traditional approaches generally lack the ability to fully model uncertainty and hesitation in complex decision-making processes. This necessitates advanced decision sets, such as the IVN approach proposed in this study, to fill this methodological gap.

3. Methodology

The decision-making process involves many uncertainties due to insufficient and incomplete information, abstract concepts, and linguistic expressions of decisions. Fuzzy sets have been proposed to efficiently tackle such uncertainty [23]. Fuzzy sets were later developed as interval-valued fuzzy sets to assign more values to the degree of membership [35]. It was developed by Atanassov [36] to include both membership and non-membership information. However, these sets did not give the desired results in representing uncertainty [37].

Neutrosophic sets, which are an improved version of intuitionistic fuzzy sets (IFSs), are represented by the degree of membership, each of which is defined over the interval (0, 1), with the total of the lower bounds of all parameters not exceeding three. These parameters are the degree of membership, the inconsistency, and the degree of non-membership. As can be understood from these parameters, neutrosophic clusters contain uncertain and inconsistent information. Fuzzy sets contain incomplete and imprecise information. However, if the information obtained is both inconsistent and contradictory, both fuzzy sets and neutrosophic sets are insufficient to evaluate the information. For this reason, a hybrid version of both sets has been developed [38].

This research employs IVNSs to support decision-making processes in inconsistent and uncertain environments. In addition, the IVN-SWARA method is used to determine the importance of the criteria, and the IVN-EDAS method is utilized to rank the alternatives. In the rest of this section, the preliminaries of IVNSs will be explained. Then, the IVN-SWARA and EDAS methodology will be explained.

3.1. *Fundamentals of IVNSs*

Definition 1. Eq (1) demotes $N(x)$, which stands for an IVN number (IVNN) denoted by three parameters. These are the membership $T_N(x)$, indeterminacy $I_N(x)$, and non-membership $F_N(x)$, such that they take value in the interval [0, 1], where $T_N = \left[T_{N(x)}^{L}, T_{N(x)}^{U} \subseteq [0,1]\right], I_N(x) = \left[I_{N(x)}^{L}, I_{N(x)}^{U} \subseteq [0,1]\right]$, and $F_N(x) = \left[F_{N(x)}^{L}, F_{N(x)}^{U} \subseteq [0,1]\right]$.

$$N(x) = \left\{\langle x, \left[T_{N(x)}^{L}, T_{N(x)}^{U}\right], \left[I_{N(x)}^{L}, I_{N(x)}^{U}\right], \left[F_{N(x)}^{L}, F_{N(x)}^{U}\right]\rangle \mid x \in X\right\}. \tag{1}$$

Definition 2. Let $a = [T_a^L, T_a^U], [I_a^L, I_a^U], [F_a^L, F_a^U]$ and $b = [T_b^L, T_b^U], [I_b^L, I_b^U], [F_b^L, F_b^U]$ be two IVNNs. Using these numbers, mathematical calculations are made below [39]:

$$a^c = \langle\left[T_a^L, T_a^U\right], \left[1 - I_a^L, 1 - I_a^U\right], \left[F_a^L, F_a^U\right]\rangle, \tag{2}$$

$$a \oplus b = \langle[T_a^L + T_b^L - T_a^L T_b^L, T_a^U + T_b^U - T_a^U T_b^U], [I_a^L I_b^L, I_a^U I_b^U], [F_a^L F_b^L, F_a^U F_b^U]\rangle, \tag{3}$$

$$a \otimes b = \langle \begin{matrix} \left[T_a^L T_b^L, T_a^U T_b^U\right], \left[I_a^L + I_b^L - I_a^L I_b^L, I_a^U + I_b^U - I_a^U I_b^U\right], \\ \left[F_a^L + F_b^L - F_a^L F_b^L, F_a^U + F_b^U - F_a^U F_b^U\right] \end{matrix} \rangle. \tag{4}$$

Definition 3. The n-dimensional IVNN weighted averaging (IVNNWA) operator, denoted by $Y = (y_1, \dots, y_i, \dots, y_n)$, as the weight vector in Eq (5), is employed to sum n IVNNs, where $(\sum_{i=1}^{n} y_i = 1)$ [40]:

$$IVNNWA(x_1, \dots, x_i, \dots, x_n) = \sum_{i=1}^{n} y_i x_i = \langle\left[1 - \prod_{i=1}^{n}(1 - T_i^L)^{y_i}, 1 - \prod_{i=1}^{n}(1 - T_i^U)^{y_i}\right], \left[\prod_{i=1}^{n}(I_i^L)^{y_i}, \prod_{i=1}^{n}(I_i^U)^{y_i}\right], \left[\prod_{i=1}^{n}(F_i^L)^{y_i}, \prod_{i=1}^{n}(F_i^U)^{i}\right]\rangle. \tag{5}$$

Definition 4. The deneutrosophication of an IVNN can be done through Eq (6) [12]:

$$\mathfrak{D}(A) = \left(\frac{(T_A^L + T_A^U)}{2} + \left(1 - \frac{(I_A^L + I_A^U)}{2} \right) \left(I_A^U \right) - \left(\frac{(F_A^L + F_A^U)}{2} \right) \left(1 - F_A^U \right) \right). \tag{6}$$

3.2. SWARA technique

The SWARA technique is a reliable subjective approach to assessing the significance of criteria [41]. This method is easier to understand and apply than other important determination techniques. This method produces a compromise solution by using individual decisions made directly by DMs [12, 42]. The application of this method consists of several steps. First, it ranks the criteria in descending order of importance. Subsequently, the relative importance value and the comparative importance value are calculated. Then, comparative coefficients are computed. Finally, revised criteria weights are found.

In the following, the execution steps of the classical SWARA technique are described:

Step 1. Depending on the objective of the problem, a set of criteria is created.

Step 2. Criteria in the given set are from highest to lowest priority.

Step 3. A relative value x_o between [0, 1] is allocated to each criterion $(o = 1, \dots, m)$.

Step 4. The criteria's relative importance is calculated using Eq (7):

$$s_o = \begin{cases} 0, & o = 1, \\ x_{o-1} - x_o & o > 1. \end{cases} \tag{7}$$

Step 5. The comparison coefficient of each criterion is determined using Eq (8):

$$k_o = \begin{cases} 1, & o = 1, \\ s_o + 1, & o > 1. \end{cases} \tag{8}$$

Step 6. Now, the revised weights are obtained through Eq (9):

$$q_o = \begin{cases} 1, & o = 1, \\ \frac{q_{o-1}}{k_o}, & o > 1. \end{cases} \tag{9}$$

Step 7. The final criteria weights of the criteria are obtained and normalized using Eq (10):

$$w_o = \frac{q_o}{\sum_{o=1}^{m} q_o}. \tag{10}$$

3.3. Fuzzy EDAS technique

The EDAS model was first proposed by Ghorabaee et al. [43] and later extended by Wang et al. [44] to trapezoidal fuzzy numbers (FNs) and adapted to fuzzy decision-making environments. This method evaluates the suitability of decision alternatives using two distance measures: average positive distance (PDA) and average negative distance (NDA). Alternatives with a high PDA value and a low NDA value are considered to be the most suitable. The EDAS model provides more consistent results by taking into account the elements of uncertainty and the intangible dimensions in the DMs' judgments, compared to the common MCDM models such as ELimination and Choice Expressing Reality (ELECTRE), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Grey Relational Analysis (GRA), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Interactive Multi-Criteria Decision-Making (TODIM), and Multi-Objective Optimization by Ratio Analysis plus the Full Multiplicative Form (MULTIMOORA) [14]. Moreover, this method has attracted wide attention due to its ability to produce effective results when dealing with conflicting criteria. By computing the average value for each criterion, the final ranking is established, thus reducing the uncertainty in the evaluations and minimizing the effect of bias [14].

In the following, the execution steps of fuzzy EDAS will be explained. Let us assume that we have H DMs; $D = \{D_1, D_2, \dots, D_h, \dots, D_H\}$, m decision criteria $C = \{C_1, C_2, \dots, C_o, \dots, C_m\}$, and n alternatives $X = \{X_1, X_2, \dots, X_i, \dots, X_n\}$. Let all DMs have the same weight.

Step 1. Linguistic assessments are obtained from the DMs about the significance of the criteria and the performance of the alternatives based on the specified criteria. These linguistic assessments are subsequently represented using the equivalent FNs.

Step 2. The aggregated decision matrix is computed using Eqs. (11) and (12):

$$X^{avg} = [\tilde{x}_{io}]_{m\times n}, \tag{11}$$

$$\tilde{x}_{io} = \frac{1}{KH} \overset{H}{\underset{h=1}{\oplus}} \tilde{x}_{iok}. \tag{12}$$

Here, $\tilde{x}_{iok}$ is the FN corresponding to the linguistic evaluation of alternative i according to criterion o by DM h.

Step 3. The criteria weight matrix is determined using Eqs. (13) and (14):

$$W^{avg} = [\widetilde{w}_o]_{1\times n}, \tag{13}$$

$$\widetilde{w}_o = \frac{1}{H} \overset{H}{\underset{h=1}{\oplus}} \widetilde{w}_{oh}. \tag{14}$$

where $\widetilde{w}_{oh}$ refers to the corresponding FN of the linguistic evaluation provided by DM h, taking into account the contribution of criterion o to the decision-making problem's objective.

Step 4. Taking into account the DMs with equal weight, the performances of each alternative according to various criteria are calculated by taking their fuzzy averages. As a result of this step, the average solution (AV) matrix is formed based on Eqs. (15) and (16):

$$AV = [\widetilde{av}_o]_{1\times n}, \tag{15}$$

$$\widetilde{av}_o = \frac{1}{n} \overset{n}{\underset{i=1}{\oplus}} \tilde{x}_{io}. \tag{16}$$

Step 5. Eqs. (17)–(20) are employed to compute the positive distance to the AV (PDA) and the negative distance to the AV (NDA) for each alternative, taking into account the criterion type:

$$PDA = \left[\widetilde{pda}_{io}\right]_{m\times n}, \tag{17}$$

$$NDA = \left[\widetilde{nda}_{io}\right]_{m\times n}. \tag{18}$$

$$\widetilde{pda}_{ij} = \begin{cases} \dfrac{\varphi(\tilde{x}_{io} \ominus \widetilde{av}_o)}{\mathfrak{H}(\widetilde{av}_o)}, & \text{if } o \in B, \\ \dfrac{\varphi(\widetilde{av}_o \ominus \tilde{x}_{io})}{\mathfrak{H}(\widetilde{av}_o)}, & \text{if } o \in C, \end{cases} \tag{19}$$

$$\widetilde{nda}_{ij} = \begin{cases} \dfrac{\varphi(\widetilde{av}_o \ominus \tilde{x}_{io})}{\mathfrak{H}(\widetilde{av}_o)}, & \text{if } o \in B, \\ \dfrac{\varphi(\tilde{x}_{io} \ominus \widetilde{av}_o)}{\mathfrak{H}(\widetilde{av}_o)}, & \text{if } o \in C. \end{cases} \tag{20}$$

The function $\varphi(.)$ yields a fuzzy zero $\tilde{0}$, when the fuzzified input value is at most zero; otherwise, it returns the input value as is. The function $\mathfrak{H}$ performs the blurring of this input.

Step 6. Eqs. (21) and (22) compute the weighted sum of the PDA and NDA per alternative, respectively:

$$\widetilde{sp}_i = \bigoplus_{o=1}^{m} (\tilde{w}_o \otimes \widetilde{pda}_{io}), \tag{21}$$

$$\widetilde{sn}_i = \bigoplus_{o=1}^{m} (\tilde{w}_o \otimes \widetilde{nda}_{io}). \tag{22}$$

Step 7. Eqs. (23) and (24) normalize the weighted sum of the PDA and NDA obtained in the previous step, respectively:

$$\widetilde{nsp}_i = \frac{\widetilde{sp}_i}{\max_i\left(\mathfrak{H}(\widetilde{sp}_i)\right)}, \tag{23}$$

$$\widetilde{nsn}_i = 1 - \frac{\widetilde{sn}_i}{\max_i\left(\mathfrak{H}(\widetilde{sn}_i)\right)}. \tag{24}$$

Step 8. The evaluation score for each alternative is obtained by calculating the fuzzy mean of $\widetilde{nsp}_i$ and $\widetilde{nsn}_i$, as follows:

$$\widetilde{as}_i = \frac{1}{2}(\widetilde{nsp}_i \oplus \widetilde{nsn}_i). \tag{25}$$

Step 9. The alternatives are prioritized from high to low on the basis of their evaluation scores.

3.4. IVN-SWARA and IVN-EDAS

Here, two main stages are provided to describe the IVN-SWARA and IVN-EDAS. Data are collected from DMs in the first stage, and then the weights of the criteria are identified by the SWARA technique. The IVN-EDAS model is utilized to assess the alternatives in the second stage. The execution steps of this hybrid methodology are described in detail below [45]:

***Phase* 1:** *IVN-SWARA*

Step 1. The sets of criteria and alternatives are specified. The DMs' weights are determined for $\lambda_h = (\lambda_1, \dots, \lambda_h, \dots, \lambda_H)$, $h = 1, \dots, H$.
Step 2. For each criterion and each alternative, DMs make a linguistic evaluation.
Step 3. With the help of the linguistic scales outlined in Table 2, the linguistic evaluations assigned to each criterion and alternative are converted into IVNNs. The IVN criterion weights matrix and decision matrices are generated as follows:

$$W = [w_{oh}]_{1\times n} \quad (h = 1, \dots, H), \tag{26}$$

$$X = [x_{ioh}]_{m\times n} \quad (h = 1, \dots, H). \tag{27}$$

Table 2. Linguistic scale used to evaluate criteria and alternatives [28].

Linguistic terms for evaluating alternatives	Code	Linguistic term for evaluating criteria	Code	$\langle \boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F} \rangle$
Certainly low	CL	Certainly low importance	VLI	⟨[0.05,0.2],[0.6,0.7],[0.75,0.9]⟩
Very low	VL	Very low importance	LI	⟨[0.15,0.3],[0.5,0.6],[0.65,0.8]⟩
Low	L	Low importance	SLI	⟨[0.25,0.4],[0.4,0.5],[0.55,0.7]⟩
Below average	BA	Below average importance	MI	⟨[0.35,0.5],[0.3,0.4],[0.45,0.6]⟩
Average	A	Average importance	SHI	⟨[0.40,0.6],[0.1,0.2],[0.40,0.6]⟩
Above average	AA	Above average importance	HI	⟨[0.45,0.6],[0.3,0.4],[0.35,0.5]⟩
High	H	High importance	VHI	⟨[0.55,0.7],[0.4,0.5],[0.25,0.4]⟩
Very high	VH	Very high importance	AHI	⟨[0.65,0.8],[0.5,0.6],[0.15,0.3]⟩
Certainly high	CH	Certainly high importance	CHI	⟨[0.75,0.9],[0.6,0.7],[0.05,0.2]⟩

Step 4. Employing the INNWA operator specified in Eq (5), the IVN matrix in Eq (26) is aggregated, resulting in the IVN criteria importance matrix shown by Eq (28):

$$W_{agg} = [w_o]_{1\times n}. \tag{28}$$

Step 5. The deneutrosophication function in Eq (6) is used to determine the criteria weights. The resulting score value is denoted as c_o.
Step 6. The obtained score values c_o are sorted in descending order for relative comparison.
Step 7. Eq (29) computes the comparative weight of each criterion (s_o):

$$s_j = \begin{cases} 0, & o = 1, \\ c_{o-1} - c_o, & o > 1. \end{cases} \tag{29}$$

Step 8. Using the values obtained in the previous step, the comparison coefficients k_o of the criteria are calculated by Eq (30):

$$k_j = \begin{cases} 1, & o = 1, \\ s_o + 1, & o > 1. \end{cases} \tag{30}$$

Step 9. The weights q_o of each criterion are revised using Eq (31):

$$q_o = \begin{cases} 1, & o = 1, \\ \dfrac{q_{o-1}}{k_o}, & o > 1. \end{cases} \tag{31}$$

Step 10. The weights of each criterion are revised using Eq (31). After normalizing the revised weights with Eq (32), the final criterion values needed for the next stage are determined:

$$w_o = \frac{q_o}{\sum_{o=1}^{m} q_o}. \tag{32}$$

***Phase* 2:** *IVN-EDAS*

Step 11. The decision matrices are normalized depending on the type of criterion [33]. The IVN matrix of the DM is organized by Eq (33):

$$X' = [x'_{ioh}]_{m\times n} = \begin{Bmatrix} \langle \left[T_{io}^{L}, T_{io}^{U}\right], \left[I_{io}^{L}, I_{io}^{U}\right], \left[F_{io}^{L}, F_{io}^{U}\right] \rangle, & if\ o \in B, \\ \langle \left[F_{io}^{L}, F_{io}^{U}\right], \left[I_{io}^{L}, I_{io}^{U}\right], \left[T_{io}^{L}, T_{io}^{U}\right] \rangle, & if\ o \in C. \end{Bmatrix} \tag{33}$$

Step 12. Eq (5) aggregates the IVN decision matrices in order to construct the matrix $\mathrm{X}'_{\mathrm{agg}}$, represented by Eq (34):

$$X'_{agg} = \left[x'_{io}\right]_{m\times n}. \tag{34}$$

Step 13. Using Eq (35), the AV for each criterion is obtained [33]:

$$AV = [AV_o]_{1\times n} = \Big\{ \langle \left[1 - \prod_{o=1}^{m}\left(1 - T_{io}^{L}\right)^{\frac{1}{m}}, 1 - \prod_{o=1}^{m}\left(1 - T_{io}^{U}\right)^{\frac{1}{m}}\right], \left[\prod_{o=1}^{m}\left(I_{io}^{L}\right)^{\frac{1}{m}}, \prod_{o=1}^{m}\left(I_{io}^{U}\right)^{\frac{1}{m}}\right], \left[\prod_{o=1}^{m}\left(F_{io}^{L}\right)^{\frac{1}{m}}, \prod_{o=1}^{m}\left(F_{io}^{U}\right)^{\frac{1}{m}}\right] \rangle \Big\}. \tag{35}$$

Step 14. The PDA and NDA of each alternative to the AV are computed through Eqs (36) and (37), respectively [33]:

$$PDA = [PDA_{io}]_{m\times n} = \left\{ \frac{max\left(0, \left(\mathfrak{D}\left(x'_{io}\right) - \mathfrak{D}(AV_o)\right)\right)}{\mathfrak{D}(AV_o)} \right\}, \tag{36}$$

$$NDA = [NDA_{io}]_{m\times n} = \left\{ \frac{max\left(0, \left(\mathfrak{D}(AV_o) - \mathfrak{D}\left(x'_{io}\right)\right)\right)}{\mathfrak{D}(AV_o)} \right\}. \tag{37}$$

Step 15. The sum of positive distance of each alternative (SP_i) and the sum of negative distance of each alternative (SN_i) are obtained with the help of Eqs (38) and (39), respectively:

$$SP_i = \sum_{o=1}^{m} w_o PDA_{io}, \tag{38}$$

$$SN_i = \sum_{o=1}^{m} w_o NDA_{io}. \tag{39}$$

Step 16. The sum of positive distances and the sum of negative distances are normalized using Eqs. (40) and (41), respectively:

$$NSP_i = \frac{SP_i}{\max_i(SP_i)}, \tag{40}$$

$$NSN_i = 1 - \frac{SN_i}{\max_i(SN_i)}. \tag{41}$$

Step 17. The appraisal score (AS) of each alternative is obtained by Eq (42), taking into account the normalized sum of the positive distances (NSP_i) and negative distances (NSN_i). The values obtained are prioritized in descending order. A high score indicates that the alternative will be preferred.

$$AS_i = \frac{1}{2}(NSP_i + NSN_i). \tag{42}$$

4. Real-world case

4.1. Problem statement

The problem addresses the criteria that healthy food companies should pay attention to when selling their products online and the evaluation of potential e-commerce platforms.

Table 3. DMs and their weights.

Code	Position	Products	Weights
DM 1	Founder of the brand	Spices, herbal teas, herbal oils, and dried fruits without irradiation, additives, or preservatives.	0.1
DM 2	Food engineer/founder of the brand	Additive-free, natural, and sustainable pasta, sauces, spices, vegetable mixes, allergy-free products, supplementary foods, and snacks.	0.1
DM 3	Founder of the brand	100% peanut and hazelnut butter without additives, preservatives, and refined sugar.	0.1
DM 4	Sales and digital marketing specialist	Natural herbal teas in high-quality, microplastic-free muslin cloths.	0.1
DM 5	Digital marketing specialist	Sports foods and supplements, such as protein powders and vitamins.	0.1
DM 6	Marketing Manager	Gluten-free products, protein bars, and healthy snacks.	0.1
DM 7	E-commerce Manager	Gluten-free, plant-based, vegan, organic, healthy snacks and foods, including raw cacao, almond flour, 100% peanut butter, and oatmeal.	0.1
DM 8	Founder of the brand/sales engineer	Healthy legumes, raw buckwheat, chia seeds, etc.	0.1
DM 9	Marketing specialist	Whole grain bread, healthy crispy bread, and crispy sandwiches.	0.1
DM 10	Founder of the brand	Healthy lavash from natural flours such as wheat flour, bran flour, and oat flour.	0.1

In this work, potential DMs were carefully evaluated on the basis of their titles within the company and their sectoral experience. The resulting group of 10 experts consists of professionals well-versed in e-commerce, including a brand founder, food engineer, sales and digital marketing specialist, marketing manager, E-commerce manager, sales engineer, and marketing specialist. Although our experts have different titles and roles, they share similar knowledge and experience in areas such as selecting B2C e-marketplaces for healthy food businesses. Therefore, to avoid any subjective hierarchical bias and to reflect the collective trend of the sector as objectively as possible, all DMs have been assigned equal weight (0.1), as presented in Table 3.

To compile the set of criteria, relevant criteria were initially identified through an extensive review of the literature. Afterward, the set of criteria was finalized through a screening process carried out by the company's managers and staff. This screening involved excluding criteria that were redundant or contradictory. Table 4 presents the descriptions and types of the selected criteria. Following the identification of the relevant criteria, seven potential e-marketplaces were chosen by consulting the DMs—Trendyol, Hepsiburada, Aliexpress, Amazon, N11, Shopier, and Çiçeksepeti—which are labeled as Alt. 1–7. Four of these alternative e-marketplaces are national, and 3 are international.

Table 4. Criteria and their types.

Criterion	Definition	Type
Cri. 1: Site traffic density	Number of visitors, number of visits, time spent on the site	Benefit
Cri. 2: Ability of sellers and consumers to interact with the site	Commenting on products, favorites, site reputation, product comparison, giving titles to sellers	Benefit
Cri. 3: Integration capability of the site	Product, order, accounting, API integration	Benefit
Cri. 4: Infrastructure strength of the site	Security (such as SSL, 3D Secure), site opening speed, ability to receive detailed sales reports, and payment infrastructure	Benefit
Cri. 5: Ease of membership conditions of the site	Membership options for buyers: elite member, VIP member, sales contract terms, and ease of contract termination	Benefit
Cri. 6: Financial structure and facilities	Site's annual turnover is high, the site works with a variety of banks, it offers discounts and coupons to sellers, it is open to international sales, and site offers a variety of payment options.	Benefit
Cri. 7: Shipping and delivery capability of the site	Low shipping fee paid by the seller, the variety of shipping companies the site works with, and the correct and timely delivery.	Benefit
Cri. 8: Usability of platform design	Site design is easy to use and understandable	Benefit
Cri. 9: Affordability of site costs	Low sales commission rates, monthly fees paid to the site for making sales, and customs tax rates	Benefit

The selection of these seven platforms (Trendyol, Hepsiburada, Aliexpress, Amazon, N11, Shopier, and Çiçeksepeti) is based on their market share dominance, high website traffic volumes, and the fact that they are the platforms preferred by most sellers and buyers. Platforms such as Trendyol, Hepsiburada, N11, and Amazon were selected due to their high market shares, while Çiçeksepeti is the leading platform in the edibles and gourmet products segment. Shopier was selected as a new platform due to its ease of access. Finally, Aliexpress was included to represent a global cross-border platform.

4.2. Numerical application

The decision-making methodology described in the previous section will be used for the selection of an internet vendor platform for healthy food producers. The seven alternative internet e-marketplace platforms were selected. DMs select the e-marketplace platform suitable for healthy food sales according to nine criteria.

Stage 1: *Preparation procedure and SWARA*

Steps 1 and 2. Decision criteria and alternatives were denoted, and the weights of the DMs were set equal. Employing the linguistic scales outlined in Table 2, the linguistic evaluation assigned to each criterion and alternative by the DMs is shown in Table 5.

Table 5. Linguistic evaluations of the DMs regarding the criteria.

Criterion	DM 1	DM 2	DM 3	DM 4	DM 5	DM 6	DM 7	DM 8	DM 9	DM 10
Cri. 1	AA	VH	VH	CH	H	VH	VH	VH	CH	VH
Cri. 2	H	VH	AA	CH	H	AA	VH	CH	VH	VH
Cri. 3	CH	H	H	CH	VH	VH	VH	VH	VH	CH
Cri. 4	AA	VH	H	CH	H	VH	VH	AA	H	AA
Cri. 5	A	H	A	VH	A	A	H	AA	VH	A
Cri. 6	A	AA	H	VH	H	H	H	AA	VH	H
Cri. 7	VH	H	H	CH	H	H	H	VH	VH	VH
Cri. 8	CH	CH	AA	CH	AA	A	H	VH	AA	AA
Cri. 9	AA	VH	H	CH	AA	VH	VH	VH	CH	VH

Steps 3–5. Using the linguistic scales in Table 2, DMs' judgments were converted into IVN numbers. DM opinions on criterion importance are merged with the INNWA operator defined in Eq (5) to build up a single IVN matrix. Table 6 presents the deneutrosophicated score values (c_o) calculated for each criterion with this matrix.

Table 6. Criteria's aggregated IVN matrix.

Criterion	$\langle \boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F} \rangle$	$\mathfrak{D}(A)$
Cri. 1	<[0.649,0.806],[0.482,0.583],[0.138,0.300]>	0.847
Cri. 2	<[0.576,0.739],[0.000,0.000],[0.000,0.000]>	0.658
Cri. 3	<[0.667,0.824],[0.505,0.606],[0.119,0.281]>	0.871
Cri. 4	<[0.582,0.741],[0.409,0.511],[0.202,0.366]>	0.757
Cri. 5	<[0.496,0.671],[0.203,0.321],[0.295,0.473]>	0.618
Cri. 6	<[0.542,0.698],[0.344,0.453],[0.253,0.411]>	0.697
Cri. 7	<[0.616,0.771],[0.455,0.556],[0.174,0.333]>	0.800
Cri. 8	<[0.538,0.713],[0.000,0.000],[0.000,0.000]>	0.625
Cri. 9	<[0.633,0.792],[0.458,0.560],[0.150,0.315]>	0.828

Steps 6–10. Criteria weights are ranked from high to low. Score values, revised weights, comparative coefficient, comparative significance values, and final criteria weights acquired from intermediate calculations are outlined in Table 7.

Table 7. Findings of the SWARA technique with the final weights of the criteria.

Criterion	Score values (c_o)	Comparative significance values (s_o)	Comparative coefficient (k_o)	Revised weights (q_o)	Final criteria weights (w_o)
Cri. 3	0.871	0.019	1.019	0.958	0.125
Cri. 1	0.847	0.000	1.000	1.000	0.122
Cri. 9	0.828	0.007	1.007	0.78	0.120
Cri. 7	0.800	0.039	1.039	0.811	0.117
Cri. 4	0.757	0.028	1.028	0.932	0.112
Cri. 6	0.697	0.060	1.006	0.843	0.106
Cri. 2	0.658	0.024	1.024	0.976	0.102
Cri. 5	0.618	0.043	1.043	0.894	0.098
Cri. 8	0.625	0.032	1.032	0.786	0.098

The three most important criteria are Cri. 3 (integration capability of the site), Cri. 1 (site traffic density), and Cri. 9 (affordability of site costs). Cri. 3 tops the list with a weight of 0.125 and emphasizes that the integration capability of a site plays a critical role in e-marketplace selection. Cri. 1 ranks second with a weight of 0.122 and shows how important the traffic density of an e-marketplace is in terms of its potential to attract customers. Cri. 9 ranked third with a weight of 0.120, which shows that cost management is a determining factor in decision-making processes.

The three least important criteria are Cri. 8 (usability of platform design), Cri. 5 (ease of membership conditions of the site), and Cri. 2 (ability of seller and consumer to interact with the site). Cri. 8, with a weight of 0.098, shows that the user-friendliness of the platform design is considered less prioritized than the other criteria. Similarly, Cri. 5, with a weight of 0.098, shows that the simplicity of membership conditions has a lower influence on the decision-making process. Cri 2, with a weight of 0.102, indicates that the interaction between the seller and the consumer is less prioritized compared to other criteria.

Stage 2: *IVN-EDAS*

Steps 11–13. The IVN decision matrices are first normalized according to Eq (6) and then combined to produce the aggregated decision matrix. Next, the AV is calculated using Eq (35) and detailed in Table 8.

Table 8. AV and the corresponding deneutrosophicated value.

Criterion	$\langle \boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F} \rangle$	$\mathfrak{D}(A)$
Cri. 1	<[0.564,0.734],[0.361,0.472],[0.204,0.385]>	0.743
Cri. 2	<[0.531,0.702],[0.352,0.464],[0.240,0.420]>	0.700
Cri. 3	<[0.543,0.714],[0.335,0.450],[0.229,0.410]>	0.713
Cri. 4	<[0.556,0.726],[0.302,0.421],[0.222,0.400]>	0.723
Cri. 5	<[0.558,0.725],[0.352,0.463],[0.218,0.393]>	0.730
Cri. 6	<[0.548,0.714],[0.324,0.437],[0.231,0.405]>	0.713
Cri. 7	<[0.505,0.670],[0.317,0.429],[0.279,0.449]>	0.656
Cri. 8	<[0.519,0.693],[0.326,0.440],[0.248,0.433]>	0.684
Cri. 9	<[0.467,0.644],[0.230,0.345],[0.310,0.496]>	0.598

Step 14. The PDA and NDA of each alternative to the AV are obtained.

Steps 15 and 16. The weighted sum of positive distances (SP_i), the weighted sum of negative distances (SN_i), the normalized positive distance (NSP_i), and the normalized negative distance (NSN_i) values are calculated in these steps and presented in Table 9.

Table 9. SP_i, SN_i, NSP_i, and NSN_i of the alternatives.

	Alt. 1	Alt. 2	Alt. 3	Alt. 4	Alt. 5	Alt. 6	Alt. 7
SP	0.255	0.113	0.000	0.074	0.001	0.000	0.008
NP	0.000	0.000	0.094	0.029	0.145	0.296	0.058
	Alt. 1	Alt. 2	Alt. 3	Alt. 4	Alt. 5	Alt. 6	Alt. 7
NSP	1.000	0.443	0.001	0.289	0.004	0.000	0.030
NSN	1.000	1.000	0.682	0.900	0.509	0.000	0.804

Step 17. The AS values of each alternative are displayed in Table 10.

Table 10. AS values computed for the alternatives.

	Alt. 1	Alt. 2	Alt. 3	Alt. 4	Alt. 5	Alt. 6	Alt. 7
AS	1.000	0.721	0.342	0.595	0.256	0.000	0.417
Rank	1	2	5	3	6	7	4

The alternatives are arranged in the following order: $\text{Alt.}1 > \text{Alt.}2 > \text{Alt.}4 > \text{Alt.}7 > \text{Alt.}3 > \text{Alt.}5 > \text{Alt.}6$. According to the suggested hybrid model, Alt. 1 (Trendyol) must be regarded as the best alternative, followed by Alt. 2 (Hepsiburada) and Alt. 4 (Amazon) as the second and third best alternatives.

5. Sensitivity assessment

In this section, a sensitivity analysis is performed in order to evaluate the effect of changing the criteria weights on the results. In this context, the weight of one criterion was raised by 100% each time, and the weights of the other criteria were decreased at equal rates so that the total weight was 100%. The analysis covers the cases of increasing the criteria weights by 100%, 200% and 300%. Therefore, two cases are defined below:

I. **100% and 200% increase:** In the first two scenarios, it was observed that the evaluation scores of the alternatives became closer to each other. However, this change did not affect the rankings. This shows that the model is generally robust to weight fluctuations.

II. **300% increase:** In the third scenario, a difference was detected. Only in the case of a 300% increase in the weight of Criterion 1, the rankings of the alternatives ranked 4th and 5th were switched. However, as can be seen from this situation, there were no major changes in the ranking.

Figure 1 visually presents the effect of a 100% increase in the weight of each criterion on the evaluation scores of the alternatives. The graph shows that the scores between the alternatives are narrowed, but the ranking remains unchanged. Table 11 details the change of ranking for Criterion 1 for a 300% increase.

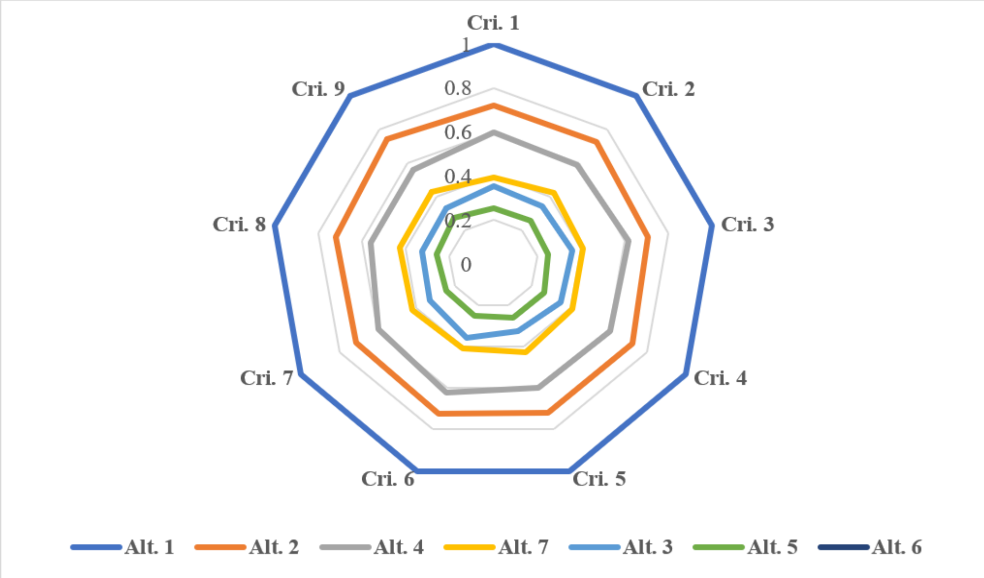

Figure 1. AS of alternatives against a 100% increase in each criterion weight.

Table 11. Comparison of the initial solution with a 300% increase scenario for the weight of Criterion 1 and evaluation scores.

Rank	Alternative	Initial score	%300 increase score	Ranking change
1	Alt.1	1.000	1.000	No change
2	Alt.2	0.721	0.721	No change
3	Alt.4	0.595	0.603	No change
4	Alt.7	0.417	0.365	↓ (-1)
5	Alt.3	0.342	0.370	↑ (+1)
6	Alt.5	0.256	0.249	No change
7	Alt.6	0.000	0.000	No change

6. Discussion and conclusion

This study analyzed the criteria taken into consideration by healthy food businesses in Türkiye when choosing B2C e-marketplaces and evaluated alternative platforms in terms of their performance. This is one of the few academic studies examining B2C e-marketplace selection from the perspective of sellers and is unique in the sense that it emphasizes the specific dynamics of healthy food businesses and the effects of these dynamics on e-marketplace selection. Findings reveal that Cri. 3 (integration capability of the site), Cri. 1 (site traffic density), and Cri. 9 (affordability of site costs) are the top three criteria when healthy food sellers select e-marketplaces. On the other hand, Cri. 2 (ability of seller and consumer to interact with the site), Cri. 5 (ease of membership conditions of the site), and Cri. 8 (usability of platform design) appears to be the least important criteria for the selection of e-marketplaces. These findings partly match those of [3,4,20,21], who found that financial factors (commission rates, monthly payments, etc.) are among the most important selection criteria. However, considering the unique needs and priorities of healthy food sellers, the integration capability of the site and site traffic density take precedence over financial concerns. First, this can be attributed to the fact that healthy food products usually have a certain expiration date, and fast delivery and accurate inventory tracking are very important for such products. Therefore, e-marketplaces with high integration capacity in terms of their ability to work with accounting, inventory, and order management systems would increase operational efficiency and minimize errors, and thus, better respond to such needs.

Second, although healthy food producers generally target a niche consumer group, they may wish to facilitate access to healthy foods for low-income consumers by choosing the right e-marketplace and thus contribute to development goals. E-marketplaces with high traffic density would increase the visibility of these products and enable them to reach a wider customer base. With the increasing awareness of healthy living, it would be easier for consumers to discover these products, therefore making it more logical to prefer e-marketplaces with high traffic density. These results would lead to a managerial implication that e-marketplaces should focus on developing their integration capabilities and implementing marketing strategies that will generate higher site traffic in order to be selected by healthy food businesses. Increased integration capabilities can be achieved by providing real-time data synchronization for a better-integrated structure, which can be implemented via cloud-based solutions and/or artificial intelligence (AI)-supported analysis tools. Additionally, technical support services, guides explaining integration processes, and online and on-site training programs can be provided so that healthy food businesses can use the technology of e-marketplaces effectively. As for the improvement of site traffic, e-marketplaces may create a strong presence on social media platforms, run advertising campaigns aimed at the target audience, offer personalized recommendations and discount campaigns by analyzing user habits, and last but not least, encourage site visits by offering special point systems, membership advantages, and discounts to consumers.

Moreover, it was revealed that Trendyol, Hepsiburada, and Amazon are the most preferred e-marketplaces by healthy food businesses, whereas Aliexpress, N11, and Shopier are the least preferred. As a managerial implication, it can be suggested that, to maintain their preferences, Trendyol, Hepsiburada, and Amazon can make continuous improvements and investments in their technological infrastructure. While global e-marketplaces like Amazon can streamline customs and international sales processes to give local healthy food businesses access to a wider market, local e-marketplaces like Trendyol and Hepsiburada can develop programs that offer more export opportunities for such businesses. On the other hand, the least preferred e-marketplaces can facilitate the operational processes of healthy food businesses by increasing their integration capacity, for instance, through Application Programming Interface (API) support. Moreover, these e-marketplaces may increase traffic density by collaborating with healthy lifestyle brands and influencers. They can also become attractive to healthy food businesses by offering cost advantages since the affordability of site costs is another important selection criterion, followed by integration capability and traffic density of the site.

This work provides applicable information not only for e-marketplace managers but also for owners and managers of healthy food businesses. The findings indicate that, unlike previous studies, businesses should look beyond low commission rates (cost factors) when selecting a sales channel and prioritize the platform's technological compatibility. As “integration capability” emerged as the most important criterion, healthy food businesses are advised to invest in ERP or inventory management systems that can seamlessly synchronize with major marketplaces such as Trendyol and Amazon. The study also offers significant contributions to the literature in terms of theoretical implications within the context of B2C e-marketplaces and healthy food businesses. Most of the existing literature has concentrated on the B2C e-marketplace selection process from a consumer point of view. However, this study applied the sellers' point of view by considering the unique needs of healthy food businesses and revealed the importance of factors such as integration capacity, site traffic density, and cost-effectiveness for such businesses. These findings fill the knowledge gap in understanding B2C e-marketplace selection processes from a business perspective and suggest that businesses of different product categories may have different selection criteria for e-marketplaces. Additionally, this research used IVN-SWARA and IVN-EDAS methods to evaluate decision-making processes based on uncertainty and conflicting information. This methodological approach offers an innovative alternative to traditional methods in literature (e.g., AHP, TOPSIS), encouraging a greater focus on uncertainty management.

Although this research presented a robust decision-making process, there are some limitations that should be considered. First, the sample size in this research was determined to be ten experts. This sample size is sufficient for MCDM methodologies (such as SWARA and EDAS); however, reaching more experts in this field could produce more generalized results. Second, this study focused on healthy food companies. However, the criteria and their importance may vary for a different food sector. Finally, the study uses IVN sets to address uncertainty. While IVN is a good option for modeling uncertainty, it requires complex computational steps. Future studies could compare these results with other extensions of fuzzy sets, such as the spherical or Pythagorean fuzzy sets, or use different MCDM models (e.g., WASPAS, VIKOR) to further validate the findings. As well as managerial and theoretical contributions, the analysis focused only on healthy food businesses in Türkiye. Even though these results provide important insights into emerging markets, they cannot be generalized to other sectors or geographic regions. The evaluation of B2C e-marketplace alternatives was limited to seven platforms, and the results could have been more comprehensive if a wider range of e-marketplaces had been examined. On the other hand, these limitations provide an opportunity for future studies. It is suggested that further research should examine the criteria of e-marketplace selection of businesses in sectors other than healthy food. It would also be useful to develop studies focusing on both business and consumer-oriented selection criteria by conducting a comparative analysis.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflict of interest.

References

1. Gelder K (2025) E-commerce worldwide – statistics & facts. Statista. Available from: https://www.statista.com/topics/871/online-shopping

2. Statista (2025) Distribution of online purchases worldwide as of April 2024, by channel. Available from: https://www.statista.com/statistics/861336/
3. Kahraman C, Onar SÇ, Öztayşi B (2018) B2C marketplace prioritization using hesitant fuzzy linguistic AHP. *Int J Fuzzy Syst* 20: 2202-2215 https://doi.org/10.1007/s40815-017-0429-4
4. Bingöl M, Karaarslan MH (2024) İşletmelerin pazaryeri seçimini etkileyen faktörlerin önem derecelerinin AHS yöntemi ile belirlenmesi. *Çağ Univ Sos Bilim Derg* 21: 70–90.
5. Dominici A, Boncinelli F, Gerini F, Marone E (2021) Determinants of online food purchasing: the impact of socio-demographic and situational factors. *J Retail Consum Serv* 60: 102473. https://doi.org/10.1016/j.jretconser.2021.102473
6. Ling S, Zheng C, Cho D (2023) How brand knowledge affects purchase intentions in fresh food e-commerce platforms. *Behav Sci* 13: 672. https://doi.org/10.3390/bs13080672
7. Liu M, Jia W, Yan W, He J (2023) Factors influencing consumers' repurchase behavior on fresh food e-commerce platforms. *Adv Eng Inform* 56: 101936. https://doi.org/10.1016/j.aei.2023.101936
8. Osaili TM, Al-Nabulsi AA, Taybeh AO, et al. (2023) Healthy food and determinants of food choice on online food delivery applications. *PLoS One* 18: e0293004. https://doi.org/10.1371/journal.pone.0293004
9. Sigurdsson V, Menon RGV, Fagerstrøm A (2017) Online healthy food experiments: capturing complexity using choice-based conjoint analysis. *Behav Anal* 40: 373–391. https://doi.org/10.1007/s40614-017-0114-9
10. Ghosh D, Roy S (2010) A decision-making framework for process plant maintenance. *Eur J Ind Eng* 4: 78–98. https://doi.org/10.1504/EJIE.2010.029571
11. Smarandache F (2005) Neutrosophic set—A generalization of the intuitionistic fuzzy set. *Int J Pure Appl Math* 24: 287–299.
12. Yazdani M, Pamučar D, Chatterjee P, Torkayesh AE (2021) A multi-tier sustainable food supplier selection model under uncertainty. *Oper Manag Res* 15: 116–145. https://doi.org/10.1007/s12063-021-00186-z
13. Koska A, Erdem MB (2023) Performance analysis of manufacturing waste using SWARA and VIKOR methods: evaluation of Turkey within the scope of the circular economy. *Sustainability* 15: 12110. https://doi.org/10.3390/su151612110
14. Demircan ML, Özcan B (2021) A proposed method to evaluate warehouse location for 3PL cold chain suppliers in Gulf countries using neutrosophic fuzzy EDAS. Int J Comput Intell Syst 14: 202. https://doi.org/10.1007/s44196-021-00041-w
15. Cakmak E, Guney E (2023) Spare parts inventory classification using neutrosophic fuzzy EDAS method in the aviation industry. *Expert Syst Appl* 224: 120008. https://doi.org/10.1016/j.eswa.2023.120008
16. Naujoks T (2020) Marketing functions and B2C e-marketplaces: an exploratory analysis. *J Mark Channels* 26: 250–262. https://doi.org/10.1080/1046669X.2020.1828687
17. Stockdale R, Standing C (2002) A framework for the selection of electronic marketplaces. *Internet Res* 12: 221–234. https://doi.org/10.1108/10662240210430900

18. Arif M, Suseno JE, Isnanto RR (2020) Multi-criteria decision-making with the VIKOR and SMARTER methods for optimal seller selection from several e-marketplaces. *E3S Web Conf* 202: 14002. https://doi.org/10.1051/e3sconf/202020214002
19. Kumar A, Sikdar P, Saha R (2021) Seller experience assessment in online marketplace: a scale development study. *Benchmarking* 28: 2315–2342. https://doi.org/10.1108/BIJ-06-2020-0305
20. Akman G, Boyacı Aİ, Kurnaz S (2022) Selecting the suitable e-commerce marketplace with neutrosophic fuzzy AHP and EDAS methods from seller's perspective in the context of Covid-19. *Int J Anal Hierarchy Process* 14. https://doi.org/10.13033/ijahp.v14i3.994
21. Çağlar S (2022) Markaların sanal pazaryeri seçiminde etkili olan faktörlerin belirlenmesi. Master's thesis. İstanbul: Bahçeşehir Üniversitesi.
22. Putri AS, Setiono M (2023) Comparative analysis of seller's preferences in selling online in marketplaces. *J Sist Tek Ind* 25: 112–125. https://doi.org/10.32734/jsti.v25i1.11209
23. Zadeh LA (1965) Fuzzy sets. *Inf Control* 8:338–353. https://doi.org/10.1016/S0019-9958(65)90241-X
24. Büyüközkan G (2004) Multi-criteria decision-making for e-marketplace selection. *Internet Res* 14: 139–154. https://doi.org/10.1108/10662240410530853
25. Ömürbek N, Şimşek A (2014) Analitik Hiyerarşi Süreci ve Analitik Ağ Süreci yöntemleri ile online alışveriş site seçimi. *J Manag Econ Res* 22: 306–327. https://doi.org/10.11611/JMER214
26. Çakır E, Akel G, Doğaner M (2018) Türkiye'de faaliyet gösteren özel alışveriş sitelerinin bütünleşik SWARA-WASPAS yöntemi ile değerlendirilmesi. *Ulus İktisadi İdari İncelemeler Derg* 599–616. https://doi.org/10.18092/ulikidince.347658
27. Ülger YT, Toksarı M (2020) E-ticaret sitelerinin kullanılabilirliği ve başarısını etkileyen faktörlerin belirlenmesi. *Giresun Univ İİBF Derg* 6: 116–128. https://doi.org/10.46849/guiibd.823445
28. Bulak ME, Kozanoğlu O, Aydoğduoğlu ŞN, Göçer F, Algül R (2021) E-ticaret sitelerinin kullanılabilirliğinin AHP ve TOPSİS yöntemleriyle karşılaştırılması. *Avrupa Bilim Teknol Derg* 26: 493–509. https://doi.org/10.31590/ejosat.963658
29. Maruf M (2021) Türkiye'de e-ticaret sitelerinin SWARA ve WASPAS yöntemleri ile web sitesi performansına göre sıralanması. *TroyAcad* 6: 411–421. https://doi.org/10.31454/troyacademy.897589
30. Erdas Y, Ecer F (2022) Covid-19 salgınında sanal alışveriş platformlarının performanslarının ölçülmesi: AHP-MAIRCA modeli. *SDÜ Vizyoner Derg* 13: 619–641. https://doi.org/10.21076/vizyoner.949281
31. Jiang H, Lin Y, Luo X, Shao T (2022) Understanding the selection of cross-border import e-commerce platforms through the DANP and TOPSIS techniques. *J Glob Inf Technol Manag* 25: 26–53. https://doi.org/10.1080/1097198X.2021.2022397
32. Özbek A, Sırakaya Ö (2022) Türkiye'de kullanılan e-ticaret platformlarının performanslarının karşılaştırılması. *Kırıkkale Univ Sos Bilim Derg* 12: 469–492.
33. Thanh VD, Van LH, Tuyet NTA, Tuan HM (2022) Using a multi-criteria decision-making model to evaluate and select an e-commerce platform. *Int J Manag Entrep Res* 4: 26–35. https://doi.org/10.51594/ijmer.v4i1.285

34. Gürbüz A, Aksu M (2023) Hangisine tıklasak acaba? Tüketici perspektifinden e-ticaret platformları: Türkiye üzerine bir araştırma. *J Soc Sci Res* 135: 135–145. https://doi.org/10.48145/gopsbad.1253469
35. Turksen IB (1986) Measurement of membership functions. In: Adv Hum Factors Ergon, Vol 6. Elsevier, Amsterdam, 55–67. https://doi.org/10.1016/B978-0-444-42723-6.50009-X
36. Atanassov KT (1986) Intuitionistic fuzzy sets. *Fuzzy Sets Syst* 20: 87–96. https://doi.org/10.1016/S0165-0114(86)80034-3
37. Torra V (2010) Hesitant fuzzy sets. Int J Intell Syst 25: 529–539. https://doi.org/10.1002/int.20418
38. Das S, Roy BK, Kar MB, et al. (2020) Neutrosophic fuzzy set and its application in decision-making. *J Ambient Intell Humaniz Comput* 11: 5017–5029. https://doi.org/10.1007/s12652-020-01828-2
39. Karaşan A, Kahraman C (2018) A novel interval-valued neutrosophic EDAS method: prioritization of the United Nations national sustainable development goals. Soft Comput 22: 4891–4906. https://doi.org/10.1007/s00500-018-3088-y
40. Zhang HY, Wang JQ, Chen XH (2014) Interval neutrosophic sets and their application in multicriteria decision making problems. *Sci World J* 2014: 645953. https://doi.org/10.1155/2014/645953
41. Keršulienė V, Zavadskas EK, Turskis Z (2010) Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). *J Bus Econ Manag* 11: 243–258. https://doi.org/10.3846/jbem.2010.12
42. Mardani A, Nilashi M, Zakuan N, et al. (2017) A systematic review and meta-analysis of SWARA and WASPAS methods. *Appl Soft Comput* 57: 265–292. https://doi.org/10.1016/j.asoc.2017.03.045
43. Ghorabaee MK, Zavadskas EK, Amiri M, Turskis Z (2016) Extended EDAS method for fuzzy multi-criteria decision-making: an application to supplier selection. *Int J Comput Commun Control* 11: 358–371. https://doi.org/10.15837/ijccc.2016.3.2557
44. Wang P, Wang JJ, Wei G (2019) EDAS method for multiple criteria group decision-making under 2-tuple linguistic neutrosophic environment. *J Intell Fuzzy Syst* 37: 1597–1608. https://doi.org/10.3233/JIFS-17922
45. Cakmak E (2023) Supplier selection for a power generator sustainable supplier park: interval-valued neutrosophic SWARA and EDAS application. *Sustainability* 15: 13973. https://doi.org/10.3390/su151813973