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Is E-Trust a Driver of Sustainability? An Assessment of Turkish E-Commerce Sector with an Extended Intuitionistic Fuzzy ORESTE Approach

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Abstract: Due mainly to COVID-19 and the demanding work schedules of many individuals, online purchasing sites have become indispensable. However, the dynamic online environment and everchanging customer demands make sustainable competitiveness challenging for e-commerce platforms. Humans primarily influence the preference for online purchase platforms. This study aimed to discover Türkiye's top popular online shopping sites by adopting an extended intuitionistic fuzzy ORESTE (Organisation, Rangement Et Synthèse De Données Relationnelles) approach. Our study targeted this by surveying female users of four online shopping platforms using IF-ORESTE. The criteria were determined according to customer preferences. These were as follows: easy accessibility to the platform, providing regular discounts and campaigns, advanced filtering settings, the contractual merchants' reliability, quick delivery, being more affordable than competing platforms, positive feedback in user comments, having a large brand volume, having an installment option, and having partnered cargo companies. The least important factor was the large volume of brands on the online websites. Quick delivery of orders and positive feedback in reviews were equally important. Similarly, the decision-makers considered regular discounts and promotions and the comprehensive filtering settings as equally critical. However, these criteria were less significant than quick delivery and positive customer feedback. This work's novelty lies in implementing the IF to the ORESTE in the Turkish e-commerce industry. The implications and future directions are discussed.

Keywords: online shopping; ORESTE; multi-criteria decision making (MCDM); intuitionistic fuzzy set; e-commerce website

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1. Introduction

A company often implements a strategic management method to be sustainable and competitive. It most certainly includes a resource-based perspective of the firm (e.g., strategies, skills, business innovation, product development, and research implications) as well as theoretical extensions such as business expert systems, knowledge development, utilization capabilities, and generating long-term (competitive) business advantages [1]. Over the last two decades, the majority of companies around the world including both small- and medium-sized enterprises (SMEs) and large corporations have attempted to develop and maintain their e-commerce websites, acknowledging that having an online presence provides numerous competitive advantages over conventional 'brick-and-mortar' rivals [2]. E-commerce is a modern business strategy that assists firms in maintaining a competitive advantage in a rapidly changing business environment by lowering customer expenses, improving the quality of goods and services provided, and speeding up the delivery process [3,4].

E-commerce, often known as electronic commerce, refers to the online purchase and sale of goods and services. This can include business-to-business (B2B), business-to-consumer (B2C), and even consumer-to-consumer (C2C) transactions on platforms such as online marketplaces. With the proliferation of the Internet and mobile technology, e-commerce has grown in popularity. It has numerous advantages including convenience, a vast assortment of products, reasonable costs, and the opportunity to shop anywhere at any time. E-commerce platforms typically consist of an online storefront or website where customers can explore products, add them to shopping carts, and complete transactions using secure payment systems. In addition, e-commerce frequently employs digital marketing strategies such as search engine optimization, social media marketing, and email marketing to contact potential customers and increase sales. The rapid growth of digital technology has completely changed how organizations run and communicate with their stakeholders. The idea of sustainability has drawn a lot of attention in recent years, reflecting the rising concerns regarding environmental, social, and economic challenges. E-trust has concurrently come to be recognized as a crucial element in determining the nature of online interactions and transactions. This study examined the connection between e-trust and sustainability, illuminating their interaction and adding to the present scholarly conversation.

In Türkiye, where digital transformation is experienced in every field, large enterprises, SMEs, society, and individuals are inevitably involved in this transformation. During the previous 20 years, buying–shopping behaviors have altered due to the growth of the e-commerce sector and the advancement of Web 2.0 technologies [5]. With ongoing advancements in Internet technology, quick access to data is expanding; as a result, the number of e-commerce websites will keep increasing, and commercial rivalry between e-commerce sites can become increasingly fierce. Due to the technological breakthrough of recent advancements, our quick acceleration into the age of available information has been substantially expanded; the number of e-commerce websites will swiftly rise, and the friction of rivalry between these sites will put business pressure to grow [6].

E-commerce volume in Türkiye is continuing to show a growing trend. E-commerce, among the most dynamic sectors, is growing and expanding at an unstoppable pace. According to the report, retail e-commerce sales in 2021 were expected to be valued at around USD 5.2 trillion worldwide [7]. Likewise, online shopping was anticipated to constitute 19.7% of the global retail sector by 2022 [8]. This indicates the dramatic changes in shopping habits. According to [9], the effects of e-commerce have transformed how people access and transmit information and purchase things. Consumer purchase habits are simplified and individualized when e-commerce is well-developed. Because of the rapid expansion of e-commerce, customers may now access information, utilize, and engage with new marketplaces and goods.

Moreover, customers have increased their willingness to find information about the items they seek online and evaluate the many benefits and offerings. This conduct contributes to the consumers' inclination to lessen their allegiance to e-commerce businesses [10]. Consumers are more linked to brands, merchants, and goods than ever before because of e-commerce.

COVID-19 especially made online Internet shopping widely attractive among people of every demographic. Because people stayed at home for a long time during the quarantine period, their time and effort were considerably reduced. As a result, Internet markets and websites became increasingly popular, and people's reliance on online technology is still growing [11].

The reasons for those who prefer online shopping can be listed as follows: advantageous prices, discount options, same-day delivery, saving on time, the opportunity to compare products and prices, payment convenience, product variety, ease, convenience shopping, and ease of product replacement and refund.

However, along with the benefits of online shopping, some challenges can cause consumers to be confused and make the right choices. Because of the lack of face-to-face encounters with shops and untrustworthy information in virtual environments, online purchasing can present more obstacles than offline shopping [12]. For example, because of the difficulties connected with Internet purchases, establishing online loyalty is more challenging than establishing offline loyalty.

Low customer switching expenses (e.g., preventing the potential of the physical effort required to transit to another store), distrust [12,13], quick word-of-mouth dissemination [12], ease of information seeking and price comparison at competing stores [13,14], and ambiguity (e.g., insufficient details in product assessment procedures and making informed decisions, trust in online retailer, displeased processes) [12–14] are some examples.

Hence, decision making has become one of the most critical strategies in online purchasing. A decision denotes an action or series of actions chosen from many alternatives.

In the decision-making process, the fact that many factors and objectives must be evaluated together can complicate the decision-making function due to the general conflict of objectives. Organizations using modern decision support methods gain a significant competitive advantage in an increasingly complex business environment. When the chain of decisions of individuals or institutions is considered a cycle, the factors that ensure the formation of this cycle are as follows: decision-maker(s), decision environment (constraints), objectives (criteria, targets), alternatives, resources, and method [15].

From the consumer's point of view, the decision-making process is when a consumer chooses the most suitable online platform or a few available alternatives. Companies must offer high-quality websites that give both attractiveness and utility to consumers to succeed in such a company setting. Consequently, there is an underlying necessity to comprehend all parts of e-commerce websites to achieve the essential apex of appealing functioning [16]. In addition, e-marketplaces need to be aware of the critical success factors that bring them sustainable competition on the web as well as identify the factors that customers consider when purchasing goods or services online. Furthermore, the decision-making process is not always straightforward and can be influenced by various external factors such as cultural, social, and economic factors. For instance, a consumer's decision to purchase a product might be influenced by their cultural background, personal preferences, or social status. Therefore, understanding the decision-making process and the factors that influence it is crucial for businesses to develop effective marketing strategies and target the right audience.

Nevertheless, evaluating e-commerce websites is an MCDM issue since it requires examining qualitative and quantitative elements [17]. Several MCDM approaches require data on the MCDM problem's criteria and choices such as weights, order connections, and preference functions [18].

The literature has a wide variety of MCDM techniques of which the most well-known methods are the AHP, TOPSIS, DEMATEL, VIKOR, ANP, CODAS, MARCOS, PROMETHEE, and EDAS.

The MCDM methods that sort in the set of alternatives are known as outranking methods in the literature. A wide variety of methods sort in MCDM methods: ELECTRE, PROMETHEE, QUALIFLEX, REGIME, ORESTE, ARGUS, EVAMIX, and MELCHIOR.

Although different MCDM methods have many uses, the ORESTE method has been applied less than the others. Therefore, this study examined the most preferred online shopping platforms utilizing the ORESTE method, which is in the outranking class of MCDM approaches. Although the ORESTE approach is an effective decision-making tool, it cannot represent fuzziness or ambiguity. As a result, a fuzzy expansion is essential to render the approach more competent.

Hence, the study proposed an extended ORESTE method under the intuitionistic fuzzy (IF) environment. In order to understand the success factors of Turkish e-commerce platforms, the following research questions were answered:

- What is the most critical factor for Turkish customers when shopping online via e-commerce websites?
- Which marketplace is mostly preferred?

To the best of our knowledge, this study serves as the initial effort to implement the IF to the ORESTE approach, which has been absent in the literature in the setting of the Turkish e-commerce industry.

2. Literature Review

The literature part of this study was organized into two subheadings. The first category included research on e-commerce websites that employed MCDM methods, while the second contained studies that employed the ORESTE approach.

2.1. E-Commerce Websites Related Studies

E-commerce is a modern business technique that helps organizations compete in a fast-paced market by lowering customer costs, raising the quality of the products and services given, and shortening the delivery period [3,4]. The advent of e-business has resulted in alterations in how customers make decisions: it lets users quickly evaluate items, compare prices, gather information, exchange purchasing experiences with others, and complete purchases in minutes [19,20].

Prior research on e-commerce has mainly concentrated on satisfaction or website quality. For example, the authors in [21] investigated the customers' satisfaction with online shopping using the Apriori and Naive Bayes algorithms. Some authors have examined the influential factors on satisfaction with online shopping such as the experience of the customers [22], the age of the consumers [23], consumer shopping habits [24,25], consumer traits [19], safety and trust [26], social influence [27,28], nations [29], and product and service quality factors [30].

On the other hand, website quality is vital and has received a lot of attention in the e-commerce literature because numerous elements impact the customers' actions and techniques when evaluating products online [31]. The web shopping experience includes using various web-based decision-support systems for finding, comparing, and evaluating items and services in the online environment, which positively impacts the perception and assessment of products on the web [32].

As a result, many scholars have concentrated on the service quality of websites, and most of them have utilized the SERVQUAL framework developed by [33,34] or its extension models to assess the quality of the e-commerce website (e.g., [35–37]).

Several studies have been conducted to evaluate the quality and performance of e-commerce websites using MCDM methods. For instance, [38] evaluated e-commerce websites in male and female consumers utilizing fuzzy AHP, which was then fed into TOPSIS for the final evaluation. In [39], the authors introduced an E-SERVQUAL (E-S-QUAL) based fuzzy hierarchical TOPSIS.

In [40], a hybrid MCDM approach was used that included AHP and TOPSIS to rank e-WS in the e-alliance, while [41] analyzed three of Türkiye's most well-known e-commerce websites using the suggested AHP based on a fuzzy triangular scale that incorporated both the positive and negative fuzzy numbers and fuzzy VIKOR. Another study considered six major e-commerce websites in India as alternatives, and 17 significant criterion elements that impacted online purchasing the most were analyzed. The AHP and fuzzy TOPSIS were used to evaluate the websites [42]. To assess e-commerce websites, [43] presented a DEMATEL model under the single-valued trapezoidal neutrosophic sets (SVTNSs) and integrated an information-collecting module. In [44], the study extended an e-commerce success model that included criteria such as refund policy, online customer feedback, valance, supportiveness, and personalization, and then prioritized the alternative e-WS using an extended incorporating AHP and TOPSIS technique. The authors of [17] evaluated the performance of e-commerce websites using a hybrid model of the AHP and IF TOPSIS. In contrast, five critical criteria for selecting the best e-marketplace for merchants were identified, and eight online alternative e-marketplaces were analyzed using the neutrosophic fuzzy AHP, and EDAS approaches were used in another study [45].

2.2. Studies Employed the ORESTE Method

ORESTE was developed by M. Roubens in 1979. The ORESTE approach is one of the sorting techniques. The ORESTE method is used less than ELECTRE and PROMETHEE, which are outranking methods in which it is classified. After the first use of the ORESTE method by M. Roubens, Roubens showed the cornerstones of ORESTE in an article in 1980. In 1982, he used ORESTE in a case study and then explained it in a study.

The ORESTE approach includes ordinal data, criterion rankings based on significance, and alternate scores for each criterion. The ORESTE method has several advantages: it is handy when the decision-maker cannot offer precise assessment data and criteria values [46,47]. The ORESTE technique does not need the quantification of criterion weights and options, but rather their ordinal evaluation (ranking) when building global preference structures on alternative solutions [46]. By establishing relationships and dependencies between the data, the method reduces redundancy and helps prevent data inconsistencies from updating data in multiple locations. It is user-friendly, easy to learn, and requires little technical expertise to use effectively.

Since IF-ORESTE is a ranking method based on the relationship of being senior, being critical, and being preferred, it has a high level of applicability to the research topic.

The ORESTE method has been used in the literature for different decision problems as given in Table 1.

Table 1. The studies related to the ORESTE method in the literature.

Authors	Year	Application Area	Fuzziness	ORESTE Method	
				Single	Combined Method
[48]	1991	Comparing different financing strategies for nuclear waste burial scenarios		X	
[46]	2002	Sensor selection		X	
[49]	2008	ICT-research-center ranking	Fuzzy	X	
[50]	2009	ICT-research-center ranking	Fuzzy		TOPSIS
[51]	2009	Project prioritization		X	
[52]	2011	Agricultural decision		X	
[18]	2011	Analyzing economic activities for Turkish manufacturing industry			MAPPAC
[47]	2012	Material selection		X	
[53]	2013	Prioritization of grain discharging processes risks	X		Shannon's Entropy
[54]	2014	Personnel selection		X	
[55]	2016	Assessment and selection of transportation companies and suppliers		X	
[56]	2017	Selection of web design companies		X	
[57]	2018	Quality function development	Probabilistic linguistic term sets	X	
[58]	2018	Optimal innovative sharing bike design selection	Continuous interval-valued linguistic term	X	
[59]	2018	Patient prioritization	Intuitionistic multiplicative preference model	X	
[60]	2018	Determination of the most effective fuel types		X	AHP

Table 1. *Cont.*

Authors	Year	Application Area	Fuzziness	ORESTE Method	
				Single	Combined Method
[61]	2019	Assessment of venture capital investment companies	Hesitant fuzzy	X	
[62]	2019	Prioritizing the elective surgery patient admission	Hesitant fuzzy	X	
[63]	2021	Assessment of regional energy efficiency	Pythagorean fuzzy sets via conversions to intuitionistic fuzzy	X	
[64]	2021	Supplier selection	fuzzy		AHP
[65]	2021	Risk assessment	Interval Type-2 Fuzzy		FMEA
[66]	2022	Selection of order picking systems	Pythagorean fuzzy	X	
[67]	2022	Assessment of rockburst risk in the Kaiyang phosphate mine	Trapezoidal fuzzy	X	
[68]	2022	Engineering characterization prioritization	Hierarchy hesitant fuzzy		QFD
[69]	2022	Assessment of regional economic restorability	Interval type-2 fuzzy	X	
[70]	2023	Site selection for waste-to-energy system	interval type-2 fuzzy	X	

As seen from Table 2, no studies have examined e-commerce websites with the ORESTE method under an intuitionistic fuzzy environment. Hence, this study contributes to both the e-commerce and MCDM literature by assessing websites and proposing an extended IF-ORESTE method.

Table 2. IF linguistic terms for the evaluation of criteria.

Fuzzy Linguistic Descriptor	Abbreviation	Intuitionistic Fuzzy Number		
		μ	ν	π
Very Important	VI	0.90	0.10	0.00
Important	I	0.75	0.20	0.05
Medium	M	0.50	0.45	0.05
Unimportant	U	0.35	0.60	0.05
Very Unimportant	VU	0.10	0.90	0.00

It is still challenging to express uncertainty in complex decision-making problems using classical sets. This issue is resolved by the fuzzy sets theory, first presented by Zadeh [71] in 1965, and permits partial membership in a set. Triangular, trapezoidal, and bell-shaped numbers, among others, can be used, thanks to this theory. Computation with phrases, a fuzzy set theory extension, was developed to codify natural language specification [72].

The intuitionistic fuzzy set (IFS) [73] expands the traditional Fs ideal for dealing with ambiguity. IFSs are utilized in a wide range of research. The authors in [74] proposed IF-AHP, [75] used IF in the GRA, and [76] proposed IF-TOPSIS for the supplier selection problem. In addition, IF-TOPSIS was used for the sustainable supplier selection problem by [77] and to assess the airline website quality [78]. The authors in [79] preferred to use PROMETHEE for the investment bank problem in an IF environment, while [80] utilized it for offshore wind power station site selection. In [81], numerous choices for the location selection of an approved dismantling facility for end-of-life vehicles using IF CODAS were evaluated to assist in waste management and address their problem. IF VIKOR was utilized for the robot selection problem [82] and renewable energy sources [83] while [84] proposed the MARCOS method under an IF environment for ranking insurance companies in health care. For the side selection of the hydrogen mobility roll-up problem, [85] utilized IF with the WASPAS, COPRAS, and EDAS methods.

3. Method

3.1. Collection of Data

In a competitive industry, marketing to female consumers swiftly boosts revenue, market dominance, and profitability.

Nearly 85% of all consumer expenditure in the U.S. is controlled by women, and they also make 70% of the big financial decisions that affect them and their family members [86]. The reasons why the female consumer market is more profitable are:

1. Higher customer satisfaction compared to men;
2. Better return on marketing investments.

Since the rate of e-commerce usage is very high for women, this study set a female constraint as gender.

Teens and young people have the edge over older generations when it comes to Internet purchasing since they have rapidly become accustomed to the world of online shopping. Older generations are unlikely to purchase online since they are unfamiliar with the new setting and adapt more slowly to the new environment. According to one study [26], online shoppers aged 25–34 years old preferred Internet stores due to the reduced pricing and wider selection of items.

A questionnaire was prepared with the help of Google Forms, and is given in the Supplementary Materials. Five Turkish female experts (DM_1, DM_2, DM_2, DM_4, DM_5) were requested to provide the first preferred criteria value and rate the websites according to the criteria. These were heavy buyers from online marketplaces, thus, they have a lot of information in which to evaluate online marketplaces. The decision-makers' importance was determined by ranking them according to their shopping frequency. When people do not shop frequently, they might not be able to assess the websites accurately, even if they correctly define the importance degree of the criteria. The detailed information related to decision-makers is given in Table 5. The criteria weights might considerably influence the evaluation outcome. Nevertheless, crisp numbers are problematic for accurately representing criteria weights in complicated contexts. Experts, on the other hand, may perform subjective judgments between criteria.

- This is why the experts' importance ranking to their shopping frequency was first defined in linguistic terms and then translated into the IF numbers.
- Their expressions regarding the criteria and alternatives were encoded into intuitionistic fuzzy numbers (IFNs) in Tables 2 and 3 [76]. Table 2 was used to perform the language evaluations for the criteria, and Table 3 for the alternatives.

Table 3. IF linguistic terms for rating the e-commerce websites.

Fuzzy Linguistic Descriptor	Abbreviation	Intuitionistic Fuzzy Number		
		μ	ν	π
Extremely Good	EG	1	0	0
Very Very Good	VVG	0.90	0.10	0.00
Very Good	VG	0.80	0.10	0.10
Good	G	0.70	0.20	0.10
Medium Good	MG	0.60	0.30	0.10
Fair	F	0.50	0.40	0.10
Medium Bad	MB	0.40	0.50	0.10
Bad	B	0.25	0.60	0.15
Very Bad	VB	0.10	0.75	0.15
Very Very Bad	VVB	0.10	0.90	0.00

Each decision-maker was weighted, and after their assessments, all individual choice views were merged into a group opinion throughout the group decision-making process to develop an aggregated IF decision matrix.

Gender and age constraints and customer preference criteria are also important determinants in choosing an online shopping platform. Consumers place their orders from online shopping sites by paying attention to many criteria.

These criteria are listed in Table 4:

Table 4. The influential criteria of the websites.

Criteria	Sources
Easy accessibility to the platform	[26,41,87]
Providing regular discounts and campaigns	[88–92]
Having advanced filtering settings	[93,94]
The contractual merchants' reliability	[30,95–97]
Quick delivery	[30,41,90]
Being more affordable than competing platforms	[41,42]
Positive feedback in user comments	[26,41,87,98]
Having a large brand volume	[41,90]
Having an installment option	[87,90]
Having partnered cargo companies	[26,41,87]

3.2. The IF ORESTE Methodology

- The IF-ORESTE method was introduced in this study and the IF-ORESTE workflow is demonstrated in Figure 1 below. The IF-ORESTE methodology consists of three stages. The stages are explained in the following subsections.

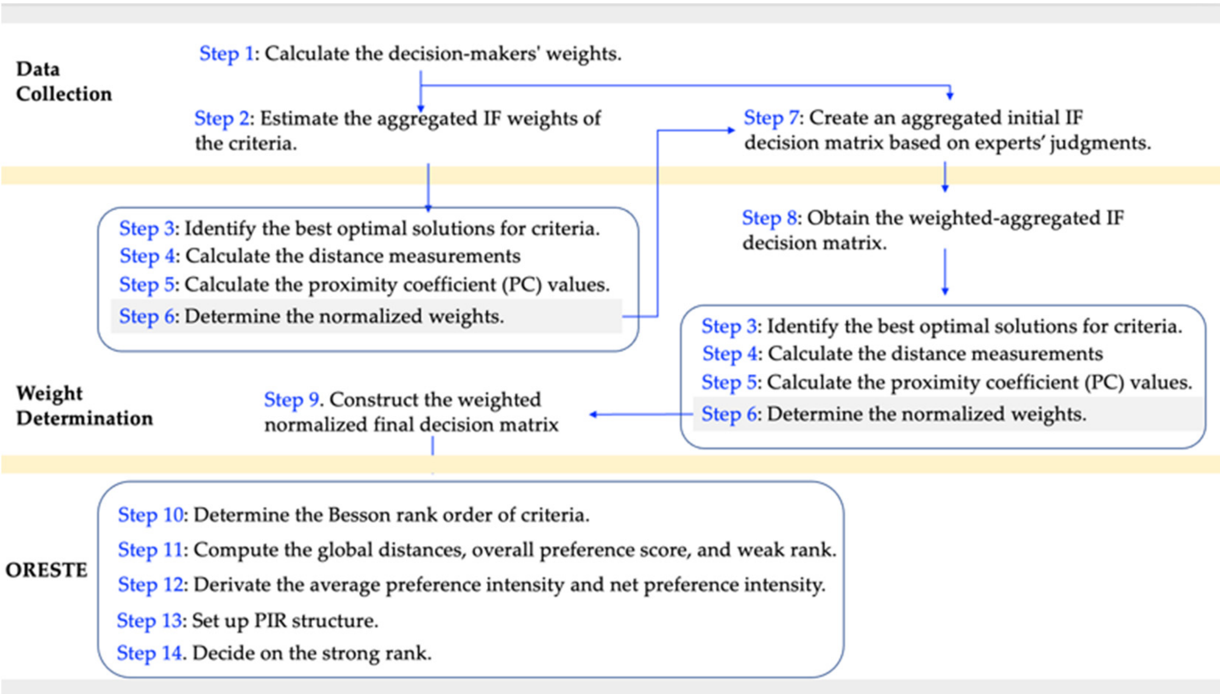

Figure 1. Stepwise IF-ORESTE method.

The first two steps were performed in the first stage, which covered the experts' evaluations of the criteria and alternatives. Thus, in the second stage, to calculate the weight of each criterion concerning Xu's IF method, the IF-weighted averaging operator (IFWA) was utilized in this research. The process is explained in the next parts. Steps 3 to 9 were conducted in this stage. The criteria weights and the final decision matrix were obtained from this stage and utilized in the third stage, where the ORESTE method was applied.

3.3. The Classical ORESTE Method

There are two separate stages in solving decision-making problems with ORESTE [51]. First, establishing a global full preliminary ranking of alternatives based on the order of the alternatives depending on the criteria with the criterion order (ORESTE I) and second, establishing a partial pre-ranking on alternatives after performing contradiction and indifference analyses (ORESTE II).

Step 1: Determining the decision problem.

In the ORESTE method, two clusters are created. The first is a set of options with m elements; A = (a_1, a_2, a_3, . . . , a_m) is the finite alternative set. The second is the finite set of criteria C = (c_1, c_2, c_3, . . . , c_k), which has k elements and is expressed as the criteria set.

For example, let the alternative set consist of three alternatives:

A = (a_1, a_2, a_3)

The set of criteria consists of three criteria:

C = (c_1, c_2, c_3) clusters will be evaluated.

Step 2: Determination of relative importance by preliminary ranking.

The weights show the relative importance of the criteria in rank. Their general structure is the preferred structure. There are two groups: preorder and weak order. The relationship between the criteria in the preliminary ranking is as follows: S = (P or I). P (preference), asymmetric, expresses the criterion's preference over the other criterion; I (indifference) shows a symmetrical relationship, meaning that there is no difference between that criterion and the other criterion.

In the same way, this relative ranking, which is j = (1, 2, 3, . . . , k) among the criteria, is made to comprehend the structure of the alternatives according to the criteria. The ultimate goal is to establish a global preference structure that shows the assessment results of alternatives according to each criterion in cluster A.

Continuous example: First of all, a preference structure will be established to determine the relative importance of the criteria. In this step, the criteria are listed in order of importance from the largest to the smallest, and the relations between the criteria are expressed as symmetrical or asymmetrical.

c_1 P c_2 I c_3

When the order and relationships of the criteria are shown as follows: criterion 1 is preferred to criterion 2 and criterion 3, criterion 2 and criterion 3 are indifferent to each other.

Likewise, in the case where the relative significance of the alternatives is explained as follows:

c_1: a_1 I a_2 P a_3

c_2: a_1 P a_1 P a_3

c_3: a_1 P a_2 I a_3

If we consider the c_1 criterion, alternatives a_1 and a_2 are preferred to alternative a_3 but are indifferent to each other.

Step 3: Determination of Besson rank values.

At this stage, the Besson rank values should be found. After defining the relative significance of the criteria and alternatives by preliminary ranking, the Besson rank values should be determined to digitize the evaluations to be used in the analysis.

The Besson rank system assigns criteria and alternatives to the criteria and alternatives in order of importance, according to their rank values. If there is a preference between the criteria or alternatives (P, asymmetric relationship), the rank values are assigned directly according to the order in which they are found. If there is indifference between the criteria or alternatives (I, symmetrical relationship), the rank values are calculated with the arithmetic mean of the ranks of the criteria/alternatives.

Continuous example:

$r(c_1) = 1$

$rc1(a_1) = \frac{1+2}{2} = 1.5$ $rc_1(a_2) = 1.5$ $rc_1(a_3) = 3$

Considering the c_1 criterion, the relative ranking value between the criteria equals the rank value and is 1.

Considering the alternatives of the c_1 criterion, this is computed by averaging the ranking values.

Step 4: Calculation of projection distances.

By considering the rank values of the alternatives/criteria, it is possible to determine the positions of the alternatives according to a selected origin point.

R = 1: Average rank (weighted arithmetic mean);

R = −1: Rank based on harmonic mean;

R = 2: Rank based on quadratic mean;

R = −∞: min((r(c_i), $rc_i(a_j)$));

R = +∞: max (r(c_i), $rc_i(a_j)$).

Projection values are calculated according to Equation (1) below:

$$DR_i(a_j) = \left(\frac{1}{2} \cdot rc_i^R + \frac{1}{2} \cdot rc_i(a_j)^R \right)^{\frac{1}{R}} \tag{1}$$

Continuing the example:

If we take the c_1 criterion and a_1 alternative in the example, the r(c_i) values are the following.

$r(c_1) = 1$ and $rc_1(a_1) = 1.5$.

The projection value for the a_1 alternative of the c_1 criterion is as follows:

$$DR_1(a_1) = (\frac{1}{2} \,.\, (1)^1 + \frac{1}{2} \,.\, (1.5)^1)^{\frac{1}{1}} = 1.25$$

Step 5: Determination of global ranks ($r(a_{ij})$),

The step of calculating global ranks consists of assigning Besson rank values to all of the calculated projection distances. The projection distances calculated using Equation (1) in the previous step were ordered from smallest to largest and took the Besson rank values according to the order in which they were found.

Step 6: Determination of average ranks.

In the step of calculating the average ranks, the global ranks obtained in the previous step were obtained by summing them for each alternative. Then, Equation (2) was used to determine the average ranks:

$$r(A_j) = \sum_{i=1}^{n} r(a_i) \tag{2}$$

After addressing the IFS rules, the IF-ORESTE method was detailed stepwise.

Preliminaries:

In a finite set U, IFS of G with the parameters $\mu_G(u)$ membership, and $\nu_G(u)$ non-membership function may be expressed as in Equation (3):

$$G = \{ \langle u, \mu_G(u), \nu_G(x) \rangle | u \epsilon U \}$$

where U: [0,1] and

$$0 \le \mu_G(u) + \nu_G(u) \le 1 \tag{3}$$

$\pi_G(u)$ is the hesitation degree in the IFS and is used to define u's belongingness to G, where $0 \leq \pi_G \leq 1$ for each $u \epsilon U$.

$$\pi_G(u) = 1 - \mu_G(u) - \nu_G(u) \tag{4}$$

When the $\pi_G(u)$ is small, there is higher certainty regarding u. When $\pi_G(u)$ is large, information about u becomes increasingly questionable. Clearly, the conventional fuzzy set idea is restored when $\mu_G = 1 - \nu_G(u)$ for all elements of the universe.

If A and B are two IFSs in U, then the multiplication operator is characterized as follows [73]:

$$A \otimes B = \{\mu_A(u)\cdot\mu_B(u)\cdot\nu_A(u) + \nu_B(u) - \nu_A(u)\cdot\nu_B(u) | u \in U\} \tag{5}$$

In the following part, the IF ORESTE method was introduced stepwise.

3.4. IF-ORESTE Method

Let $A = (A_1, A_2, \ldots, A_m)$ symbolize a group of options and $U = (U_1, U_2, \ldots, U_n)$ represent a set of criteria, and the approach for the IF-ORESTE technique is as follows:

Step 1: Calculate the decision-makers' weights.

Suppose the decision group has l experts. The decision-makers' importance is seen as linguistic phrases conveyed in intuitionistic fuzzy numbers. The fundamental definitions for the procedures employed are provided in [76].

Assume $E_t = [\mu_p, \nu_p, \pi_p]$ to be an IF number of the pth expert rating. The weight of the pth expert was then calculated as follows:

$$\gamma_p = \frac{\left(\mu_p + \pi_p\left(\frac{\mu_p}{\mu_p + \nu_p}\right)\right)}{\sum_{p=1}^{l}\left(\mu_p + \pi_p\left(\frac{\mu_p}{\mu_p + \nu_p}\right)\right)} \tag{6}$$

and $\sum_{p=1}^{l} \gamma_p = 1$.

Step 2: Estimate the aggregated IF weights of the criteria.

Not all criteria might be of equal relevance, and W characterizes a hierarchy of significance. All of the various experts' judgments on the relevance of each criterion must be combined to reach W.

Let $\omega_j{}^{(p)} = IFWA_\gamma\left[\mu_j{}^{(p)}, \nu_j{}^{(p)}, \pi_j{}^{(p)}\right]$ be an IF number applied to criteria u_j by the pth expert. The weights of the criterion were then computed utilizing the IFWA operator:

$$\begin{aligned}\omega_j &= IFWA_\gamma\left(\omega_j^{(1)}, \omega_j^{(2)}, \ldots, \omega_j^{(l)}\right) = \gamma_1\omega_j^{(1)} \oplus \gamma_2\omega_j^{(2)} \oplus \ldots \oplus \gamma_l\omega_j^{(l)} \\ &= \left[1 - \prod_{p=1}^{l}\left(1 - \mu_j^{(p)}\right)^{\gamma_p}, \prod_{p=1}^{l}\left(\nu_j^{(p)}\right)^{\gamma_p}, \prod_{p=1}^{l}\left(1 - \mu_j^{(p)}\right)^{\gamma_p} - \prod_{p=1}^{l}\left(\nu_j^{(p)}\right)^{\gamma_p}\right]\end{aligned} \tag{7}$$

$\mathcal{W} = [\omega_1, \omega_2, \omega_3, \ldots, \omega_j]$, where $\omega_j = (\mu_j, \nu_j, \pi_j)$ for every j = 1, 2, ... , n.

Step 3: Identify the best optimal solutions.

Many authors have suggested score and accuracy functions for the defuzzification of IF sets. For example, [99] considered only the membership $(\check{\mu}_{ij})$ and non-membership $(\check{\nu}_{ij})$ degrees, but the hesitancy $(\check{\pi}_{ij})$ was ignored [100]. To overcome this issue, D_i^+ and D_i^- were specified using max and min operators in the literature because their outputs had no notable disparities [84,85].

The IF has a positive ideal solution (D_i^+), which is ρ^{++} = (1, 0, 0), and a negative ideal solution (D_i^-), which is ρ^- = (0, 1, 0).

Step 4: Calculate the distance measurements.

The distance measure was calculated using the fuzzy normalized Euclidean distance function [101]. In Equations (8) and (9), D_i^+ and D_i^- represent the positive and negative distance metrics, respectively.

$$D_i^+ = \left(\sqrt{(\check{\mu}_i - \rho^+)^2 + (\check{v}_i - \rho^+)^2 + (\check{\pi}_i - \rho^+)^2}\right) \tag{8}$$

$$D_i^- = \left(\sqrt{(\check{\mu}_i - \rho^-)^2 + (\check{v}_i - \rho^-)^2 + (\check{\pi}_i - \rho^-)^2}\right) \tag{9}$$

Step 5: Calculate the proximity coefficient (PC) values.

The PC is defined as follows using the equation below [84].

$$PC_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{10}$$

Step 6: Determine the normalized weights.

To obtain the final decision matrix, the PC values must be normalized. For normalization, Equation (11) below was utilized.

$$W(C_j) = \frac{p_j}{\sum_{i=1}^{m} p_i},\ j = 1, \ldots, n \tag{11}$$

where $\sum_{j=1}^{n} W(C_j) = 1$.

Step 7: Create an aggregated initial IF decision matrix based on the experts' judgments.

Let $D^p = \left(d^{(p)}{}_{ij}\right)_{m\times n}$ represent each expert's IF decision matrix. $\gamma = \{\gamma_1, \gamma_2, \gamma_3, \ldots, \gamma_l\}$ denotes the weight of each expert, and $\sum\limits_{p=1}^{l} \gamma_p,\ \gamma_p \in [0,1]$. All individual preference views must be combined into a group opinion throughout the decision-making stage to develop an aggregated IF decision matrix. The IFWA operator introduced by [102] was employed to do this.

$D = (d_{ij})_{m\times n}$, where

$$\begin{aligned} d_{ij} &= IFWA_\gamma\left(d_{ij}^{(1)}, d_{ij}^{(2)}, \ldots, d_{ij}^{(l)}\right) = \gamma_1 d_{ij}^{(1)} \oplus \gamma_2 d_{ij}^{(2)} \oplus \ldots \oplus \gamma_l d_{ij}^{(l)} \\ &= \left[1 - \prod_{p=1}^{l}\left(1-\mu_{ij}^{(p)}\right)^{\gamma_p}, \prod_{p=1}^{l}\left(v_{ij}^{(p)}\right)^{\gamma_p}, \prod_{p=1}^{l}\left(1-\mu_{ij}^{(p)}\right)^{\gamma_p} - \prod_{p=1}^{l}\left(v_{ij}^{(p)}\right)^{\gamma_p}\right] \end{aligned} \tag{12}$$

$d_{ij} = \left(\mu_{A_i}(u_j), v_{A_i}(u_j), \pi_{A_i}(u_j)\right)$ for each i = 1, 2, … , m and j = 1, 2, … , n.
The following is the aggregated IF decision matrix:

$$D = \begin{bmatrix} (\mu_{A_1}(u_1), v_{A_1}(u_1), \pi_{A_1}(u_1)) & \cdots & (\mu_{A_1}(u_n), v_{A_1}(u_n), \pi_{A_1}(u_n)) \\ \vdots & \ddots & \vdots \\ (\mu_{A_m}(u_1), v_{A_m}(u_1), \pi_{A_m}(u_1)) & \cdots & (\mu_{A_m}(u_n), v_{A_m}(u_n), \pi_{A_m}(u_n)) \end{bmatrix} = \begin{bmatrix} d_{11} & d_{12} & \ldots & d_{1m} \\ d_{21} & d_{22} & \ldots & d_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \ldots & d_{nm} \end{bmatrix}$$

Step 8: Obtain the weighted-aggregated IF decision matrix.

The aggregated IF decision matrix is formed when the criteria weights ($\mathcal{W}$) and the aggregated IF decision matrix are estimated [73]:

$$D \otimes \mathcal{W} = \left\{\left\langle u, \mu_{A_i}(u).\mu_{\mathcal{W}}(u), v_{A_i}(u) + v_{\mathcal{W}}(u) - v_{A_i}(u).v_{\mathcal{W}}(u)\right\rangle \middle| u \in U\right\} \tag{13}$$

and

$$\pi_{A_i.\mathcal{W}}(u) = 1 - v_{A_i}(u) - v_{\mathcal{W}}(u) - \mu_{A_i}(u).\mu_{\mathcal{W}}(u) + v_{A_i}(u) + v_{\mathcal{W}}(u) \tag{14}$$

The aggregated weighted IF decision matrix may then be constructed, as shown below.

$$\check{D} = \begin{bmatrix} (\mu_{A_1\mathcal{W}}(u_1), \nu_{A_1\mathcal{W}}(u_1), \pi_{A_{1\mathcal{W}}}(u_1)) & \cdots & (\mu_{A_1\mathcal{W}}(u_n), \nu_{A_1\mathcal{W}}(u_n), \pi_{A_1\mathcal{W}}(u_n)) \\ \vdots & \ddots & \vdots \\ (\mu_{A_m\mathcal{W}}(u_1), \nu_{A_m\mathcal{W}}(u_1), \pi_{A_m\mathcal{W}}(u_1)) & \cdots & (\mu_{A_m\mathcal{W}}(u_n), \nu_{A_m\mathcal{W}}(u_n), \pi_{A_m\mathcal{W}}(u_n)) \end{bmatrix} = \begin{bmatrix} \check{d}_{11} & \check{d}_{12} & \ldots & \check{d}_{1j} \\ \check{d}_{21} & \check{d}_{22} & \ldots & \check{d}_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ \check{d}_{i1} & \check{d}_{i2} & \ldots & \check{d}_{ij} \end{bmatrix}$$

$\check{d}_{ij} = \check{\mu}_{ij}, \check{\nu}_{ij}, \check{\pi}_{ij} = (\mu_{A_i\mathcal{W}}(u_j), \nu_{A_i\mathcal{W}}(u_j), \pi_{A_i\mathcal{W}}(u_j))$ describes a component of the aggregated weighted IF decision matrix.

Step 9: Construct the weighted normalized final decision matrix.

The ultimate weights were computed with normalization. To normalize the weighted IF values, the steps were followed to determine the final weights of the criteria (steps 3 to 6). The normalized value can be obtained using Equations (8)–(11).

Step 10: Determine the Besson rank order of criteria.

The weighted normalized final decision matrix $\check{d}_{ij}$ was obtained from step 9 of the methodology. The final normalized matrix values were ranked in ascending order. Based on the Besson rank orders connected with the k criteria, each option was assigned a rating for each criterion. Furthermore, each criterion was allotted a rating depending on its position in the criteria's weak order.

Step 11: Compute the global distances, overall preference score, and weak rank.

The global distances were calculated using Equation (1). For each alternative under each criterion, the global preference score was calculated by multiplying the criteria weight with the global distance for each alternative and corresponding criterion. The values of rc_i^R were given the final weights of criteria ($\mathcal{W}$) from step 6. After obtaining the global scores, the weak order of alternatives was determined. The summation of the global scores related to the criteria for each alternative indicates the weak rank of alternatives. The scores were ranked in descending order. The highest score took the last weak order. The first weak rank of the alternative took the higher preference degree.

Step 12: Derive the average preference intensity and net preference intensity.

The average and net preference intensities are needed to build the PIR (preference, indifference, and incomparability) structure. The average preference intensity A_i to A_g can be processed using Equation (15) and the net preference intensity as per Equation (16) below.

$$F(A_i, A_g) = \frac{\sum_{j=1}^{n} \max((r(a_{gj}) - r(a_{ij})), 0)}{(m-1)\cdot k^2} \tag{15}$$

$$\Delta F(A_i, A_g) = F(A_i, A_g) - F(A_g, A_i) \tag{16}$$

Step 13: Set up the PIR structure.

Initially, the principles of the indifference and incomparability examination (i.e., the conflict analysis) can be specified as follows:

1. When $|\Delta F(A_i, A_g)| \geq \mu$, then $\begin{cases} A_i\ P\ A_g,\ if\ \Delta F(A_i, A_g) > 0 \\ A_g\ P\ A_i,\ if\ \Delta F(A_i, A_g) \leq 0 \end{cases}$;
2. When $|\Delta F(A_i, A_g)| < \mu$, then

$$\begin{cases} A_i\ I\ A_g,\ if\ F(A_i, A_g) < \sigma\ and\ F(A_g, A_i) < \sigma; \\ A_i\ R\ A_g,\ if\ at\ least\ one\ criterion\ does\ not\ meet\ the\ condition \end{cases}'$$

where μ and σ are the preference and indifference threshold parameters, respectively, and $\in [0,1]$. The parameters μ and σ can be determined using Equations (17) and (18), respectively.

$$\mu = \frac{\delta}{n} \tag{17}$$

$$\begin{cases} \sigma = \dfrac{(n+2)\delta}{2n}, & if\ n\ is\ odd \\ \sigma = \dfrac{\delta}{2}, & if\ n\ is\ even \end{cases} \tag{18}$$

where δ is the preference intensity indifference threshold and is computed as follows:

$$\delta = \sqrt{\xi} * \frac{\varepsilon}{2\beta} \tag{19}$$

The parameter "ε" is the indifference relation with the minimum difference between two linguistic terms and is calculated from practical problems. More information about the selection of the parameters can be found in [58].

Step 14: Decide on the strong rank.

The outcome is a common choice depending on the weak rank and the PIR structure. The weak rank and the PIR structure determine the alternative's substantial rank. The rank of specific alternatives is calculated based on the P and I relations in the PIR structure. Then, the total rank may be inferred by integrating the weak rank when the R connection is present amongst many other possibilities. For example, if the weak rank of four choices is $A_1 > A_2 > A_3 > A_4$ and the PIR associations are as follows: A_1 P A_2, A_1 P A_3, A_1 P A_4, A_2 I A_3, A_2 P A_4, and A_3 R A_4 are then found using the P and I relations in the PIR structure. $A_1 > A_2$ because A_1 P A_2, $A_1 > A_3$ because A_1 P A_3, $A_1 > A_4$ because A_1 P A_4, $\{A_2, A_3\}$ because A_2 I A_3, and $A_2 > A_4$ because A_2 P A_4, but the rank of options A_3 and A_4 cannot be immediately established by the PIR relations for A_3 R A_4. In this scenario, the low ranking of options A_3 and A_4 might be used as a guide. Because $A_3 > A_4$ is in the weak rank, the entire rank of possibilities is $A_1 > \{A_2, A_3\} > A_4$, and the strong rank is $A_1 > \{A_2, A_3\} > A_4$.

4. Results and Discussion

The four most popular Turkish e-commerce websites were rated according to the provided criteria by professional users.

IF-ORESTE Results

The IF-ORESTE approach was proposed and implemented in this part to examine the priorities of online consumers regarding the influencing criteria on their purchase choices from these websites. More detail about professional users can be seen in Table 5.

Table 5. The weight of the decision-makers.

	DM_1	DM_2	DM_3	DM_4	DM_5	SUM
Age	25–34	35–44	35–44	45–54	25–34	
Experience	Between 3 and 4 years	More than 5 years	More than 5 years	More than 5 years	Less than one year	
Shopping Frequency	Several times a month	Several times a month	Each week	Several times a week	Several times a month	
Rank	4	3	2	1	5	
Importance Degree	U	M	I	VI	VU	
Weight of DMs	0.3684	0.5263	0.7895	0.9000	0.1000	2.684
Normalized Weight of DMs	0.1373	0.1961	0.2941	0.3353	0.0373	1.000

It is clear from Table 5 that the most important expert was DM_4 and ranked first, while the fifth expert was ranked last because she purchased products less than the others from the Internet. The ranking was first determined by their shopping frequency. In the case when two or more experts had equal shopping frequency such as DM_1, DM_2, and DM_4, they were then ranked by their years of shopping experience. After ranking, the IF linguistic terms related to the criteria (Table 2) and alternatives (Table 3) were assigned to the corresponding decision-makers based on rank. The weight of the experts was calculated with the help of Equation (6), and then the weights of experts were normalized. The assessments of the decision-maker related criteria and alternatives are given in Tables S1 and S2, respectively, as shown in the Supplementary Materials.

Linguistic terms were turned into IF numbers. Using Equation (7), the aggregated IF criteria weights were computed, as seen in Table 6.

Table 6. The aggregated IF decision matrix with the criteria weights.

Criteria Definition	Code	μ	π	ν
Easy accessibility to the platform	C_1	0.897	0.001	0.103
Providing regular discounts and campaigns	C_2	0.858	0.004	0.138
Having advanced filtering settings	C_3	0.851	0.008	0.141
The contractual merchants' reliability	C_4	0.900	0.000	0.100
Quick delivery	C_5	0.860	0.011	0.129
Being more affordable than competing platforms	C_6	0.791	0.034	0.175
Positive feedback in user comments	C_7	0.864	0.010	0.126
Having a large brand volume	C_8	0.621	0.015	0.364
Having an installment option	C_9	0.814	0.007	0.179
Having partnered cargo companies	C_{10}	0.833	0.008	0.159

The positive and negative ideal solution and weight of the criteria are depicted in Table 6. After determining the positive and negative ideal values using Equations (8) and (9), the proximity coefficients (*PCW*) based on Equation (10), which are the weight of the indicators, were calculated. These weights were then averaged with Equation (11) to obtain the final weights of the criteria as seen in Table 7.

Table 7. The criteria weight.

Criteria		D_i^+	D_i^-	PCW	Normalized C(W)
Easy accessibility to the platform	C_1	0.146	1.004	0.873	0.107
Providing regular discounts and campaigns	C_2	0.198	1.005	0.836	0.102
Having advanced filtering settings	C_3	0.205	1.002	0.830	0.102
The contractual merchants' reliability	C_4	0.141	1.005	0.877	0.108
Quick delivery	C_5	0.191	0.997	0.839	0.103
Being more affordable than competing platforms	C_6	0.274	0.981	0.781	0.096
Positive feedback in user comments	C_7	0.186	0.998	0.843	0.103
Having a large brand volume	C_8	0.526	1.051	0.666	0.082
Having an installment option	C_9	0.259	1.009	0.796	0.098
Having partnered cargo companies	C_{10}	0.231	1.004	0.813	0.100

The criteria weights were as follows: $W = \{C_1 = 0.107, C_2 = 0.102, C_3 = 0.102, C_4 = 0.108, C_5 = 0.103, C_6 = 0.096, C_7 = 0.103, C_8 = 0.082, C_9 = 0.098, C_{10} = 0.100\}$. From Table 7, the most important criterion was C_4, which represents the reliability of contracted sellers in the online marketplace. This finding complies with other studies because [103,104] also found that trust was the most critical factor when online shopping. Building e-trust could potentially increase the use of e-commerce among the people in Türkiye.

Easy access to e-commerce platforms was the second important factor for online purchasers. The importance of easy access to the platform was also shown in the findings of [105]. However, there are various reasons for differences in online shopping behavior.

Factors such as gender, experience, and education level can impact the consumers' online shopping behavior and expectations for convenience; for example, women have different motivations than men, with females being more likely to shop online for emotional reasons and to use more interactive websites. Consumers with more experience have higher expectations for convenience and expect retailers to upgrade their websites continually.

The criteria "quick delivery" and "positive feedback in user comments" ranked behind easy access to e-commerce platforms.

Quick delivery (C_5) and positive feedback in user comments (C_7) were equally crucial to the decision-makers. In [30], the authors found that quick delivery was one of the causes of e-WOM (electronic-word of mouth). Indeed, [106] demonstrated a strong relationship between e-WOM and trust-based purchasing behavior. In [107], they also highlighted that trust had an indirect but still significant impact on women's intention to shop online.

Another finding is that providing regular discounts and campaigns (C_2) and the advanced filtering settings of websites (C_3) are equally crucial when choosing an online marketplace. The studies by [108,109] agreed that discounts were an effective way to entice new customers to shop and maintain the loyalty of regular customers. Although discount codes may decrease revenue for the store, they can potentially significantly increase the conversion rates.

The large number of users and products can make it difficult for consumers to find the right product and understand the descriptions. The solution to this issue is the recommender system, which predicts a user's preferences based on history and provides product recommendations that meet their needs [110]. Several e-commerce websites like Netflix (movie recommendations), Amazon (purchase suggestions), and Yelp (business reviews) personalize their content to enhance the user experience and increase sales, but personalization can be used for price steering or discrimination such as with travel company Orbitz, which ranked hotels higher based on the users' operating systems. The tools to detect this conduct are still lacking, making identifying personalization on e-commerce sites challenging [111].

Using information filtering and retrieval, recommender systems are crucial in offering personalized services, extracting item features, and modeling the users' interests to suggest relevant products to customers. The system aims to minimize the search costs and make it easier for customers to find what they want by taking explicit and implicit feedback into account [112].

The criteria "having partnered cargo companies" and "having an installment option" ranked before the criterion of whether the online marketplace had various brands, which ranked as the least significant factor when choosing an e-commerce platform.

E-payment involves electronic payment methods used for online transactions conducted over the Internet. This can refer to a payment process that does not involve cash but uses digital means to complete the transaction. The distribution of e-commerce payment methods can differ from country to country; for example, in Indonesia in 2021, the e-payment methods consisted of using mobile banking or Internet banking to transfer funds, making online credit card transactions, using electronic wallets, and installment payments [113]. In Türkiye, a customer may use an installment plan to pay for any accommodation-related service if the seller agrees, but it is not permitted for food-related purchases. E-commerce vendors who use a marketplace model for their operations must be aware of all such limitations [114,115].

The least significant criterion was whether the online shopping platform offered various brands.

After weighing the criteria, the initial aggregated IF decision matrix was constructed using Equation (12). With the help of Equations (13) and (14), the weighted aggregated IF decision matrix was built. The values related to the membership degrees of the initial IF decision matrix are presented in Table S3, as seen in the Supplementary Materials, and the weighted aggregated IF decision matrix is presented in Table 8.

Table 8. The weighted aggregated μ, ν, and π values of the alternatives for each criterion.

	C1			C2			C3			C4			C5		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
A1	0.563	0.408	0.029	0.544	0.424	0.033	0.476	0.427	0.097	0.508	0.387	0.105	0.545	0.374	0.081
A2	0.897	0.103	0.001	0.858	0.138	0.004	0.851	0.141	0.008	0.900	0.100	0.000	0.648	0.311	0.040
A3	0.542	0.425	0.032	0.548	0.420	0.032	0.454	0.438	0.107	0.479	0.416	0.105	0.475	0.418	0.106
A4	0.505	0.442	0.053	0.508	0.463	0.029	0.421	0.449	0.130	0.500	0.380	0.121	0.422	0.445	0.133
	C6			**C7**			**C8**			**C9**			**C10**		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
A1	0.791	0.175	0.034	0.864	0.126	0.010	0.621	0.364	0.015	0.538	0.376	0.086	0.576	0.365	0.059
A2	0.791	0.175	0.034	0.864	0.126	0.010	0.621	0.364	0.015	0.814	0.179	0.007	0.833	0.159	0.008
A3	0.555	0.393	0.052	0.487	0.405	0.108	0.390	0.516	0.094	0.480	0.408	0.112	0.556	0.392	0.052
A4	0.483	0.472	0.045	0.466	0.410	0.124	0.357	0.549	0.094	0.814	0.179	0.007	0.535	0.409	0.056

The fuzzy numbers indicate the values corresponding to the alternatives under the provided criteria. The defuzzification process was followed similarly to the identification of the criteria. With the help of Equations (8)–(10), the fuzzy numbers were turned to crisp values. The proximity coefficients for each alternative related to the criteria, which presents the overall score (*PCW*), are depicted in Table S4 in the Supplementary Materials.

After obtaining the final weighted decision matrix, these values were averaged utilizing Equation (11). The normalized weighted final scores for alternatives under the given criteria are exhibited in Table 9.

Table 9. The normalized weighted decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.225	0.223	0.221	0.22	0.26	0.3	0.31	0.3	0.21	0.23
A_2	0.35	0.343	0.36	0.35	0.29	0.3	0.31	0.3	0.3	0.32
A_3	0.218	0.225	0.214	0.21	0.23	0.22	0.19	0.21	0.19	0.22
A_4	0.207	0.209	0.205	0.22	0.22	0.19	0.19	0.19	0.3	0.22
Sum	1	1	1	1	1	1	1	1	1	1

The following steps were handled with the same respect as the basic ORESTE steps. The final values for each alternative corresponding to the criteria and the criteria weights were obtained from Tables 7 and 9, respectively. Each alternative under each given criterion was assigned a Besson rank ($R(C_i)$), as seen in Table 10 below.

Table 10. The Besson rank of alternatives under the criteria.

	$R(C_1)$	$R(C_2)$	$R(C_3)$	$R(C_4)$	$R(C_5)$	$R(C_6)$	$R(C_7)$	$R(C_8)$	$R(C_9)$	$R(C_{10})$
A_1	2	3	2	2	2	1.5	1.5	1.5	3	2
A_2	1	1	1	1	1	1.5	1.5	1.5	1.5	1
A_3	3	2	3	4	3	3	3	3	4	3
A_4	4	4	4	3	4	4	4	4	1.5	4

After determining the distances for the alternatives to the criteria by means of Equation (1), the global preference scores were computed by multiplying the criteria weight. The weak ranks of the alternatives were acquired using global distances. The R coefficient was chosen as 1. The results are presented in Table S5 in the Supplementary Materials. The global scores are shown in Table 11. The sum of all criteria scores under each alternative was computed, and the mean rank was determined. The mean ranks were A_1 = 3.693, A_2 = 3.257, A_3 = 4.214, and A_4 = 4.487.

Table 11. The global scores.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	Sum
A_1	0.214	0.435	0.382	0.161	0.283	0.503	0.258	0.470	0.537	0.449	3.693
A_2	0.161	0.333	0.331	0.108	0.232	0.503	0.258	0.470	0.464	0.399	3.257
A_3	0.268	0.384	0.432	0.269	0.334	0.575	0.336	0.531	0.586	0.498	4.214
A_4	0.321	0.487	0.483	0.215	0.386	0.623	0.388	0.572	0.464	0.548	4.487

The lower the average preference score, the better the option. The choices were arranged as follows: $A_2 \succ A_1 \succ A_3 \succ A_4$.

The intensity of the preferences was used to detect conflicting positions to discriminate between indifference and incomparability. With the help of Equation (15), the preference intensities and their normalized values were calculated. The preference intensity matrix and averaged preference intensity matrix are given in Table S6 in the Supplementary Materials, and Table 12 is presented below.

Table 12. Normalized preference intensity matrix.

	A_1	A_2	A_3	A_4
A_1	0.0000	0.0000	0.0019	0.0029
A_2	0.0015	0.0000	0.0032	0.0041
A_3	0.0002	0.0000	0.0000	0.0015
A_4	0.0002	0.0000	0.0006	0.0000

The PIR structure was formed centered on the preference and indifference thresholds. In this study, the parameter was selected as $\delta = 0.01$. Based on this parameter, the preference and indifference thresholds were calculated using Equations (17) and (18). Then the preference intensity (μ) was calculated as 0.001, and the indifference threshold as $\sigma = 0.005$. The PIR structure was established based on the above-mentioned parameters and rules, as seen in Table 13.

Table 13. The PIR structure matrix.

	A_1	A_2	A_3	A_4
A_1	-	I	>	>
A_2	>	-	I	>
A_3	I	I	-	>
A_4	I	I	I	-

When the preference intensity of (A_g, A_k) is nearly equivalent to the intensity of (A_k, A_g), indifference exists if both values are modest, and a conflict scenario (incomparability) develops when both intensities are great. In such a situation, "A_g" outperforms "A_k" on one criterion set, but "A_k" outperforms "A_g" on those other criteria sets [116].

The weak rank followed $A_2 \succ A_1 \succ A_3 \succ A_4$, while the strong rank occurred as $A_2 \sim A_3 \succ A_1 \succ A_4$, which means that the best alternative was A_2.

In both rank orders, A_2 was the most preferred e-commerce platform; in contrast, A_4 was the last. The final result showed that A_3 was preferable to A_1.

5. Conclusions

The IFSs were integrated into the ORESTE approach to evaluate the four most prominent e-commerce websites in Türkiye under the specified criteria. By soliciting the opinion of professionals, the experts ranked their online shopping experience by year. Their preferences regarding e-commerce websites and the criteria were converted into IF numbers to avoid information loss. The experts' weights were derived by analyzing the variability of DMs with distinct characteristics. After establishing the criterion weights and generating the normalized weighted decision matrix, the global preference score was determined, and the conventional ORESTE method was implemented.

The most favored e-commerce platform was A_2, whereas A_4 was required from both the weak and strong IF-ORESTE rankings.

The most important criterion was the reliability of the contracted sellers in the online marketplace while having a large brand volume was the least. Easy access to e-commerce platforms was the second most important factor for online purchasers, followed by quick delivery and positive feedback in user comments. Likewise, the decision-makers valued the criteria of offering regular discounts/promotions and the extensive filtering settings of websites equally crucial but less than quick delivery and positive feedback in user comments. The criterion partnered cargo companies was found to be more significant than the e-commerce platform's installment options and its affordability compared to its rivals [30,106–115].

Trust is crucial for long-term virtual commercial interactions, influencing consumer happiness and satisfaction. Online purchasing sites must gain consumer trust, as faith positively influences satisfaction. Trust is essential for secure and trustworthy transactions, and online businesses must maintain confidence to generate consumer attention. Frequent online shopping services generate increased consumer interest in transactions [117]. In [118], it was demonstrated that the most prevalent sort of trust was when customers, as trustors, anticipated another party (typically sellers) performing an expected action, and they offered a synthesis of the theories used in the review as it can also highlight the factors that could have been more focused on such as interpreting trust by different parties.

The decision of e-commerce platforms to establish the marketplace channel is complex due to competition and cooperation. Although suppliers face challenges such as commission fees and responsibility for sales and marketing activities, they benefit from the marketplace channel, allowing them to control product pricing and directly reach online consumers [119]. The marketplace channel has been proven to be an efficient and effective transaction method. However, there have still been instances where it has been misused by certain suppliers selling counterfeit or substandard items, which ultimately negatively impact the marketplace's reputation and can harm consumers. Counterfeit products, which appear identical to real ones, are a common type of fraud across different product categories on e-commerce platforms [120].

Anti-counterfeiting measures are therefore necessary to protect the integrity of the consumer market and promote sustainable development. The blockchain anti-counterfeiting traceability system has emerged as a potential solution. It utilizes the features of blockchain technology such as distributed ledger record characteristics and the Internet of Things to trace every aspect of a product's journey from raw material sourcing to production, processing, and logistics. This system ensures the authenticity of products and creates trust between brands and consumers. E-commerce platforms can implement different service models such as building their own blockchain anti-counterfeit traceability platform or collaborating with third-party platforms to provide anti-counterfeiting traceability services to consumers. However, these different models have varying costs and efficiencies and can affect the company and consumers differently [121]. Additionally, smaller suppliers may not be able to afford the fees charged by e-commerce platforms, which could make it more challenging for them to compete with larger enterprises. Therefore, an integrated model is needed to challenge this problem.

Improved human–technology communication is essential to achieve sustainable growth in online businesses. Digital media help firms obtain marketing intelligence, incorporate knowledge into product creation and marketing plans, and obtain feedback for remedial action. Incorporating new technical tools into an enterprise's operations is critical to satisfy consumer demand and boost resilience [122]. The desire of a client to maintain their connection to a firm is determined by their view of the advantages of a high-quality service that delivers a constant flow of value [123]. However, at this fast pace, customer demands are constantly changing. Companies must offer their users high-quality websites that are interesting and functional according to their wishes in order to compete. Firms exploring electronic data interchange will find these websites to be an appealing alternative. As a result, in the growing global economy, e-commerce has evolved into an essential component of company strategy [124].

To remain competitive, e-retailers must supply special items, provide "a greater shopping environment, more customized options, and higher customer control", and ensure that the online buying experience is simple and fast [125]. A successful strategic management approach in e-commerce competitiveness necessitates a recognition of the drivers that influence the whole process [126].

To summarize, trust might be a driver as a success factor for e-commerce platforms, while positive feedback from customers might speed up the process of success.

5.1. Implications

There is an increasing importance in developing digital skills and promoting them in public education to narrow the digital divide. Policy recommendations include measures to increase ICT literacy and Internet accessibility, reduce the gender gap, improve security in online shopping, and encourage companies to focus on innovating and targeting market segments that are less likely to shop online.

The effectiveness of new e-commerce legislation in India is being questioned due to slow judicial processes, inadequate infrastructure, and corrupt practices. Consumer activists, policymakers, and researchers can collaborate to strengthen trust-building among online consumers. The research also contributes to understanding online trust and e-consumer protection as well as identifying crucial factors that affect customer loyalty. As the e-commerce industry constantly evolves, future research will be necessary to assess the effectiveness of the enacted legislation, promote trust-building, and protect consumer rights. The government's policies also pose a challenge as they accelerate online transactions, emphasizing the need to maintain consumer protection in e-commerce.

On the other hand, e-commerce has resulted in changes in consumer behavior and the value of retail space, making it essential for urban management to track changes in shop rents and understand the logic behind them. Mapping shop rent distributions is necessary to optimize retail land returns, monitor dynamic changes in shop rents, study the spatial distribution of retail facilities, and optimize the layout of shop spaces. While the impact of e-commerce on consumer behavior and retail services has been widely studied, few studies have examined the changes in shop prices or rents. One study used geospatial big data and machine learning to identify factors impacting shop rents, the new logic of rent distribution in Guangzhou, and map changes in shop rent distribution. The study revealed the impact of e-commerce on changing customer behaviors and suggests the need to rethink the pricing mechanism to define the value of urban space. Future research should focus on finer mapping and the in-depth analysis of the rent distribution mechanisms by using machine learning algorithms for causal inference [127].

Industries are adopting autonomous technology to increase production rates, but small- and medium-scaled industries face barriers when attempting to adopt such technology due to high costs and maintenance, a lack of skilled resources, increased maintenance costs, a decrease in the versatility of the technology, and an increase in unemployment as key factors [128].

5.2. Limitations and Future Works

Further study may be conducted to expand the number of alternatives and criteria, and our IF-ORESTE rankings technique can be compared with other MCDM methods. Because limited factors were considered in this research, in the following studies, more factors might be included in the analysis and the results compared with each other. Another point is that the trust and reliability terms were generally considered; however, e-trust includes many aspects such as the imitation of products or false information, etc. Hence, in future studies, this term might be specified and reanalyzed.

On the other hand, this study can be compared with other fuzzy ORESTE methods using sensitivity analysis. For example, [129] discussed different aggregating operators to assess the optimal solutions under the multi-attribute decision-making technique, specifically in handling uncertain and ambiguous information under the IF system. The authors studied triangular norms and their generalization in the form of robust aggregation tools using the Aczel Alsina operations. They developed a list of certain operators under the IF information system including the IFAAHM (intuitionistic fuzzy Aczel Alsina Heronian mean) and IFAAWHM (intuitionistic fuzzy Aczel Alsina weighted Heronian mean) operators, and extended the theory of GHM (geometric Heronian mean) tools. Since aggregating operators play a crucial role in MCDM methods, applying different aggregating operators can result in various options. Therefore, in further studies, these operators can be employed, and the findings can be compared. The study of the connection between e-trust and sustainability is crucial for the development of theories and methodologies. Through this study, we can learn important things about how e-trust influences sustainability, adding to both a theoretical understanding and real-world applications.

There is a need for a complete framework to identify critical technical requirements to improve sustainable e-commerce management practices. For example, using quality function deployment [130] or Maclaurin symmetric mean aggregation operators based on novel Frank T-norm and T-conorm for intuitionistic fuzzy multiple attribute group decision-making [131] for e-commerce industries might reveal the most important customer and critical technical requirements that can enhance a company's technical capability.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su151310693/s1, Table S1: Linguistic evaluation of decision-makers for criteria assessment. Table S2: Linguistic evaluation of decision-makers for e-commerce website assessment. Table S3: The initial aggregated μ, v, and π values of alternatives for each criterion. Table S4: The alternatives' weights for each criterion. Table S5: Global distances (R = 1). Table S6: The global scores.

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Abbreviations

AHP	Analytical hierarchal process
ANP	Analytic network process
ARGUS	An outranking method
CODAS	Combinative distance-based assessment
COPRAS	Complex proportional assessment
DEMATEL	Decision Making Trial and Evaluation Laboratory
EDAS	Evaluation based on distance from average solution
ELECTRE	Elimination et Choice Translating Reality
EVAMIX	Evaluation matrix
FMEA	Failure mode and effect analysis
GRA	Grey relational analysis
MAPPAC	Multicriterion analysis of preferences by means of pairwise actions and criterion comparisons
MARCOS	Measurement of alternatives and ranking according to the compromise solution

MELCHIOR	Methode d'Elimination et de Choix Incluant les relation d'ORdre
ORESTE	Organisation, Rangement Et Synthese de donnees relaTionnElles
PROMETHEE	Preference ranking organization method for enrichment evaluation
QFD	Quality function deployment
QUALIFLEX	The QUALItative FLEXible multiple criteria method
REGIME	An outranking method
TOPSIS	Technique of order preference by similarity to ideal solution
VIKOR	VIŠekriterijumsko KOmpromisno Rangiranje
WASPAS	Weighted aggregated sum product assessment
DM	Decision-maker

References

1. Hamilton, J. The Strategic Change Matrix and Business Sustainability across COVID-19. *Sustainability* **2020**, *12*, 6026. [CrossRef]
2. Hristoski, I.; Kostoska, O.; Kotevski, Z.; Dimovski, T. Factors Affecting the Competitiveness of E-Commerce Firms: A Critical Appraisal. In Proceedings of the International Balkan and Near Eastern Social Sciences Congress Series III. IBANESS Congress Series-Edirne/Turkey, Edirne, Turkey, 4–5 March 2017; pp. 1079–1090.
3. Ngai, E.W.T.; Wat, F.K.T. Fuzzy Decision Support System for Risk Analysis in E-Commerce Development. *Decis. Support Syst.* **2005**, *40*, 235–255. [CrossRef]
4. Thorleuchter, D.; Van Den Poel, D. Predicting E-Commerce Company Success by Mining the Text of Its Publicly-Accessible Website. *Expert Syst. Appl.* **2012**, *39*, 13026–13034. [CrossRef]
5. VanHoose, D. *Ecommerce Economics*, 2nd ed.; Taylor & Francis: Abingdon, UK, 2011; ISBN 1136821805.
6. Zhang, X.; Liu, P.; Du, Z. Research on E-Commerce Website Evaluation with Hybrid Decision-Making Index and Extension of the TOPSIS Method. In Proceedings of the 2008 Third International Conference on Pervasive Computing and Applications, Alexandria, Egypt, 6–8 October 2008; Volume 1, pp. 106–109.
7. Chevalier, S. Retail E-Commerce Sales Worldwide from 2014 to 2026. Available online: https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/ (accessed on 7 January 2023).
8. Bernhardt, G. Global Ecommerce Sales Growth Report for 2021–2026. Available online: https://www.shopify.com/blog/global-ecommerce-sales (accessed on 7 January 2023).
9. Bakshi, A.; Ujala, U.; Pyngavil, R.S. Impact of E-Commerce, Customers, Employees, Suppliers, Distributors and Competitors. *Glob. J. Enterp. Inf. Syst.* **2009**, *1*, 54–62.
10. Paștiu, C.A.; Oncioiu, I.; Gârdan, D.A.; Maican, S.Ș.; Gârdan, I.P.; Muntean, A.C. The Perspective of E-Business Sustainability and Website Accessibility of Online Stores. *Sustainability* **2020**, *12*, 9780. [CrossRef]
11. Liu, C.; Arnett, K.P. Exploring the Factors Associated with Web Site Success in the Context of Electronic Commerce. *Inf. Manag.* **2000**, *38*, 23–33. [CrossRef]
12. Zhang, T. *The Value of IT-Enabled Retailer Learning: Can Personalized Product Recommendations (PPRS) Improve Customer Store Loyalty in Electronic Markets?* University of Maryland: College Park, MD, USA, 2005.
13. Brynjolfsson Michael Smith, E.D.; Bailey, J.; Bakos, Y.; Banker, R.; Berry, S.; Hann, I.-H.; Hitt, L.; Mendelson, H.; Sorensen, A.; Bressan, S.; et al. Frictionless Commerce? A Comparison of Internet and Conventional Retailers Frictionless Commerce? *Manag. Sci.* **2000**, *46*, 563–585. [CrossRef]
14. Gefen, D. Customer Loyalty in E-Commerce. *J. Assoc. Inf. Syst.* **2002**, *3*, 27–53. [CrossRef]
15. Evren, R.; Ülengin, F. *Yönetimde Çok Amaçlı Karar Verme*; İstanbul Teknik Üniversitesi: Istanbul, Türkiye, 1992.
16. Jun, F.; Yu, L. The Evaluation of B2C E-Commerce Web Sites Based on Fuzzy AHP. In Proceedings of the Proceedings—International Symposium on Computer Science and Computational Technology, ISCSCT 2008, Shanghai, China, 20–22 December 2008; Volume 2, pp. 792–795.
17. Rouyendegh, B.D.; Topuz, K.; Dag, A.; Oztekin, A. An AH.HP-IFT Integrated Model for Performance Evaluation of E-Commerce Web Sites. *Inf. Syst. Front.* **2019**, *21*, 1345–1355. [CrossRef]
18. Dinçer, S.E. The Structural Analysis of Key Indicators of Turkish Manufacturing Industry: ORESTE and MAPPAC Applications. *Eur. J. Sci. Res.* **2011**, *60*, 6–18.
19. Melović, B.; Šehović, D.; Karadžić, V.; Dabić, M.; Ćirović, D. Determinants of Millennials' Behavior in Online Shopping—Implications on Consumers' Satisfaction and e-Business Development. *Technol. Soc.* **2021**, *65*, 101561. [CrossRef]
20. Müller, A.; Laskowski, N.M.; Wegmann, E.; Steins-Loeber, S.; Brand, M. Problematic Online Buying-Shopping: Is It Time to Considering the Concept of an Online Subtype of Compulsive Buying-Shopping Disorder or a Specific Internet-Use Disorder? *Curr. Addict. Rep.* **2021**, *8*, 494–499. [CrossRef]
21. Moon, N.N.; Talha, I.M.; Salehin, I. An Advanced Intelligence System in Customer Online Shopping Behavior and Satisfaction Analysis. *Curr. Res. Behav. Sci.* **2021**, *2*, 100051. [CrossRef]
22. Kesharwani, S.; Sharma, N. Swaying between Qualitative Information and Customers' Expectation: An Assessment of Online Shopping Sites in India. *Int. J. Inf. Technol.* **2020**, *12*, 789–795. [CrossRef]
23. Wan, Y.; Nakayama, M.; Sutcliffe, N. The Impact of Age and Shopping Experiences on the Classification of Search, Experience, and Credence Goods in Online Shopping. *Inf. Syst. e-Bus. Manag.* **2012**, *10*, 135–148. [CrossRef]

24. Chou, S.W.; Hsu, C.S. Understanding Online Repurchase Intention: Social Exchange Theory and Shopping Habit. *Inf. Syst. e-Bus. Manag.* **2016**, *14*, 19–45. [CrossRef]
25. Honkanen, P.; Olsen, S.O.; Verplanken, B. Intention to Consume Seafood—The Importance of Habit. *Appetite* **2005**, *45*, 161–168. [CrossRef]
26. Baubonienė, Ž.; Gulevičiūtė, G. E-Commerce Factors Influencing Consumers' Online Shopping Decision. *Soc. Technol. Soc. Technol.* **2015**, *5*, 74–81. [CrossRef]
27. Hung, S.-Y.; Chen, C.C.; Huang, N.-H. An Integrative Approach to Understanding Customer Satisfaction with E-Service of Online Stores. *J. Electron. Commer. Res.* **2014**, *15*, 40–57.
28. Kim, Y.A.; Srivastava, J. Impact of Social Influence in E-Commerce Decision Making. In Proceedings of the 9th International Conference on Electronic Commerce: The Wireless World of Electronic Commerce, Minneapolis, MN, USA, 19–22 August 2007.
29. Javadi, M.H.M.; Dolatabadi, H.R.; Nourbakhsh, M.; Poursaeedi, A.; Asadollahi, A.R. An Analysis of Factors Affecting on Online Shopping Behavior of Consumers. *Int. J. Mark. Stud.* **2012**, *4*, 81–98. [CrossRef]
30. Sıcakyüz, Ç. Analyzing Healthcare and Wellness Products' Quality Embedded in Online Customer Reviews: Assessment with a Hybrid Fuzzy LMAW and Fermatean Fuzzy WASPAS Method. *Sustainability* **2023**, *15*, 3428. [CrossRef]
31. Bhatnagar, A.; Misra, S.; Rao, H.R. On Risk, Convenience, and Internet Shopping Behavior. *Commun. ACM* **2000**, *43*, 98–105. [CrossRef]
32. Dennis, C.; Harris, I.; Sandhu, B. From Bricks to Clicks: Understanding the e-Consumer. *Qual. Market. Res. Int. J.* **2002**, *5*, 281–290. [CrossRef]
33. Parasuraman, A.; Zeithaml, V.A.; Berry, L.L. A Conceptual Model of Service Quality and Its Implications for Future Research. *J. Mark.* **1985**, *49*, 41–50. [CrossRef]
34. Parasuraman, A.; Zeithaml, V.A.; Berry, L. SERVQUAL: A Multiple-Item Scale for Measuring Consumer Perceptions of Service Quality. *J. Retail.* **1988**, *64*, 1.
35. Carrillat, F.A.; Jaramillo, F.; Mulki, J.P. The Validity of the SERVQUAL and SERVPERF Scales: A Meta-Analytic View of 17 Years of Research across Five Continents. *Int. J. Serv. Ind. Manag.* **2007**, *18*, 472–490. [CrossRef]
36. Ma, P.; Yao, N.; Yang, X. Service Quality Evaluation of Terminal Express Delivery Based on an Integrated SERVQUAL-AHP-TOPSIS Approach. *Math. Probl. Eng.* **2021**, *2021*, 8883370. [CrossRef]
37. Tumsekcali, E.; Ayyildiz, E.; Taskin, A. Interval Valued Intuitionistic Fuzzy AHP-WASPAS Based Public Transportation Service Quality Evaluation by a New Extension of SERVQUAL Model: P-SERVQUAL 4.0. *Expert Syst. Appl.* **2021**, *186*, 115757. [CrossRef]
38. Anand, O.; Ranjan Srivastava, P. A Comparative Gender Based Evaluation of E-Commerce Website: A Hybrid Mcdm Approach. In Proceedings of the 2015 Eighth International Conference on Contemporary Computing (IC3), Noida, India, 20–22 August 2015. [CrossRef]
39. Kang, D.; Jang, W.; Park, Y. Evaluation of E-Commerce Websites Using Fuzzy Hierarchical TOPSIS Based on E-S-QUAL. *Appl. Soft Comput. J.* **2016**, *42*, 53–65. [CrossRef]
40. Yu, X.; Guo, S.; Guo, J.; Huang, X. Rank B2C E-Commerce Websites in e-Alliance Based on AHP and Fuzzy TOPSIS. *Expert Syst. Appl.* **2011**, *38*, 3550–3557. [CrossRef]
41. Aydın, S.; Kahraman, C. Evaluation of E-Commerce Website Quality Using Fuzzy Multi-Criteria Decision Making Approach. *IAENG Int. J. Comput. Sci.* **2012**, *39*, 1.
42. Dey, S. Evaluation of Indian B2C E-Shopping Websites under Multi Criteria Decision-Making Using Fuzzy Hybrid Technique. *Int. J. Appl. Eng. Res.* **2015**, *10*, 24551–24580.
43. Liang, R.; Wang, J.; Zhang, H. Evaluation of E-Commerce Websites: An Integrated Approach under a Single-Valued Trapezoidal Neutrosophic Environment. *Knowl. Based Syst.* **2017**, *135*, 44–59. [CrossRef]
44. Aggarwal, A.G. Multi-Criteria-Based Prioritisation of B2C e-Commerce Website. *Int. J. Soc. Syst. Sci.* **2018**, *10*, 201. [CrossRef]
45. Akman, G.; Boyacı, A.İ.; Kurnaz, S. 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* **2022**, *14*. [CrossRef]
46. De Leeneer, I.; Pastijn, H. Decision Aiding: Selecting Land Mine Detection Strategies by Means of Outranking MCDM Techniques. *Eur. J. Oper. Res.* **2002**, *139*, 327–338. [CrossRef]
47. Chatterjee, P.; Chakraborty, S. Material Selection Using Preferential Ranking Methods. *Mater. Des.* **2012**, *35*, 384–393. [CrossRef]
48. Delhaye, C.; Teghem, J.; Kunsch, P. Application of the ORESTE Method to a Nuclear Waste Management Problem. *Int. J. Prod. Econ.* **1991**, *24*, 29–39. [CrossRef]
49. Mehdi, F.; Maryam, M.P. Information and Communication Technology Research Center Ranking Utilizing a New Fuzzy ORESTE Method (FORESTE). In Proceedings of the Third 2008 International Conference on Convergence and Hybrid Information Technology ICCIT 2008, Busan, Republic of Korea, 11–13 November 2008; Volume 2, pp. 737–742.
50. Fasanghari, M.; Mohamedpour, M.; Mohamedpour, M.A. A Novel Method Combining ORESTE, Fuzzy Set Theory, and TOPSIS Method for Ranking the Information and Communication Technology Research Centers of Iran. In Proceedings of the ITNG 2009—6th International Conference on Information Technology: New Generations, Las Vegas, NV, USA, 27–29 April 2009; pp. 165–170.
51. Ana, E.; Bauwens, W.; Broers, O. Quantifying Uncertainty Using Robustness Analysis in the Application of ORESTE to Sewer Rehabilitation Projects Prioritization—Brussels Case Study. *J. Multi-Criteria Decis. Anal.* **2009**, *16*, 111–124. [CrossRef]

52. Matějček, M.; Brožová, H. Multiple Attributes Analysis of Vegetable Production. In *Mathematics and Computers in Biology, Business and Acoustics*; WSEAS: Athens, Greece, 2011; pp. 27–32. ISBN 9789604742936.
53. Jafari, H. Identification and Prioritization of Grain Discharging Operations Risks by Using ORESTE Method. *Am. J. Public Health Res.* **2013**, *1*, 214–220. [CrossRef]
54. Eroğlu, E.; Yıldırım, B.F.; Özdemir, M. ORESTE Method in Multi Criteria Decision Making and Personnel Selection Application. *İ.Ü. İşletme Fakültesi İşletme İktisadi Enstitüsü Yönetim Derg.* **2014**, *76*, 81.
55. Madic, M.; Petrovic, G. Application of the ORESTE Method for Solving Decision Making Problems in Transportation and Logistics. *UPB Sci. Bull. Ser. D* **2016**, *78*, 83–94.
56. Aytaç Adali, E.; Tuş Işik, A. Ranking Web Design Firms with the ORESTE Method. *EGE Acad. Rev.* **2017**, *17*, 243–254.
57. Wu, X.; Liao, H. An Approach to Quality Function Deployment Based on Probabilistic Linguistic Term Sets and ORESTE Method for Multi-Expert Multi-Criteria Decision Making. *Inf. Fusion* **2018**, *43*, 13–26. [CrossRef]
58. Liao, H.; Wu, X.; Liang, X.; Yang, J.B.; Xu, D.L.; Herrera, F. A Continuous Interval-Valued Linguistic ORESTE Method for Multi-Criteria Group Decision Making. *Knowl. Based Syst.* **2018**, *153*, 65–77. [CrossRef]
59. Zhang, C.; Wu, X.; Wu, D.; Liao, H.; Luo, L.; Herrera-Viedma, E. An Intuitionistic Multiplicative ORESTE Method for Patients' Prioritization of Hospitalization. *Int. J. Environ. Res. Public Health* **2018**, *15*, 777. [CrossRef] [PubMed]
60. Murat Arslan, H. Determination of the Most Efficient Fuel Type with AHP and ORESTE Methods. *DİCLE Üniv. Sos. Bilim. Enst. Derg.* **2018**, *10*, 161–170.
61. Tian, Z.P.; Nie, R.X.; Wang, J.Q.; Zhang, H.Y. Signed Distance-Based ORESTE for Multicriteria Group Decision-Making with Multigranular Unbalanced Hesitant Fuzzy Linguistic Information. *Expert Syst.* **2019**, *36*, 12350. [CrossRef]
62. Li, J.; Luo, L.; Wu, X.; Liao, C.; Liao, H.; Shen, W. Prioritizing the Elective Surgery Patient Admission in a Chinese Public Tertiary Hospital Using the Hesitant Fuzzy Linguistic ORESTE Method. *Appl. Soft Comput. J.* **2019**, *78*, 407–419. [CrossRef]
63. Tao, Z.; Zhu, J.; Zhou, L.; Liu, J.; Chen, H. Multi-Attribute Decision Making with Pythagorean Fuzzy Sets via Conversions to Intuitionistic Fuzzy Sets and ORESTE Method. *J. Control. Decis.* **2021**, *8*, 372–383. [CrossRef]
64. Akman, G.; Pamuk, K.C.; Karabıçak, Ç. Yeni Ürün Geliştirme Sürecinde Bulanık AHP & ORESTE Bütünleşik Yöntemi Ile Tedarikçi Seçimi: Savunma Sanayisinde Bir Uygulama. *Bilecik Şeyh Edebali Üniv. Bilim. Derg.* **2021**, *8*, 954791. [CrossRef]
65. Zheng, Q.; Liu, X.; Wang, W. An Extended Interval Type-2 Fuzzy ORESTE Method for Risk Analysis in FMEA. *Int. J. Fuzzy Syst.* **2021**, *23*, 1379–1395. [CrossRef]
66. Yerlikaya, M.A. Bulanık Karar Verme Problemlerinde ORESTE Yöntemi ve Bir Çözüm Önerisi. *J. Optim. Decis. Mak.* **2022**, *1*, 123–133.
67. Shi, K.; Liu, Y.; Liang, W. An Extended ORESTE Approach for Evaluating Rockburst Risk under Uncertain Environments. *Mathematics* **2022**, *10*, 1699. [CrossRef]
68. Shi, H.; Mao, L.X.; Li, K.; Wang, X.H.; Liu, H.C. Engineering Characteristics Prioritization in Quality Function Deployment Using an Improved ORESTE Method with Double Hierarchy Hesitant Linguistic Information. *Sustainability* **2022**, *14*, 9771. [CrossRef]
69. Zhang, H.; Gao, H.; Liu, P. Assessment of Regional Economic Restorability under the Stress of COVID-19 Using the New Interval Type-2 Fuzzy ORESTE Method. *Complex Intell. Syst.* **2022**. [CrossRef]
70. Pan, X.H.; Wang, Y.M.; He, S.F.; Labella, Á.; Martínez, L. An Interval Type-2 Fuzzy ORESTE Method for Waste-to-Energy Plant Site Selection: A Case Study in China. *Appl. Soft Comput.* **2023**, *136*, 110092. [CrossRef]
71. Zadeh, L.A. Fuzzy Set. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]
72. Saremi, M.; Mousavi, S.F.; Sanayei, A. TQM Consultant Selection in SMEs with TOPSIS under Fuzzy Environment. *Expert Syst. Appl.* **2009**, *36*, 2742–2749. [CrossRef]
73. Atanassov, K. Intuitionistic Fuzzy Sets. *Fuzzy Sets Syst.* **1986**, *20*, 87–96. [CrossRef]
74. Xu, Z.; Liao, H. Intuitionistic Fuzzy Analytic Hierarchy Process. *IEEE Trans. Fuzzy Syst.* **2014**, *22*, 749–761. [CrossRef]
75. Wei, G.-W. Gray Relational Analysis Method for Intuitionistic Fuzzy Multiple Attribute Decision Making. *Expert Syst. Appl.* **2011**, *38*, 11671–11677. [CrossRef]
76. Boran, F.E.; Genç, S.; Kurt, M.; Akay, D. A Multi-Criteria Intuitionistic Fuzzy Group Decision Making for Supplier Selection with TOPSIS Method. *Expert Syst. Appl.* **2009**, *36*, 11363–11368. [CrossRef]
77. Memari, A.; Dargi, A.; Akbari Jokar, M.R.; Ahmad, R.; Abdul Rahim, A.R. Sustainable Supplier Selection: A Multi-Criteria Intuitionistic Fuzzy TOPSIS Method. *J. Manuf. Syst.* **2019**, *50*, 9–24. [CrossRef]
78. Çınaroğlu, E.; Zaralı, F. Evaluation of the Airline Website Quality with the Intuitionistic Fuzzy TOPSIS Method. *J. Turk. Oper. Manag.* **2022**, *6*, 1277–1296. [CrossRef]
79. Feng, F.; Xu, Z.; Fujita, H.; Liang, M. Enhancing PROMETHEE Method with Intuitionistic Fuzzy Soft Sets. *Int. J. Intell. Syst.* **2020**, *35*, 1071–1104. [CrossRef]
80. Wu, Y.; Tao, Y.; Zhang, B.; Wang, S.; Xu, C.; Zhou, J. A Decision Framework of Offshore Wind Power Station Site Selection Using a PROMETHEE Method under Intuitionistic Fuzzy Environment: A Case in China. *Ocean Coast. Manag.* **2020**, *184*, 105016. [CrossRef]
81. Karagoz, S.; Deveci, M.; Simic, V.; Aydin, N.; Bolukbas, U. A Novel Intuitionistic Fuzzy MCDM-Based CODAS Approach for Locating an Authorized Dismantling Center: A Case Study of Istanbul. *Waste Manag. Res.* **2020**, *38*, 660–672. [CrossRef]
82. Devi, K. Extension of VIKOR Method in Intuitionistic Fuzzy Environment for Robot Selection. *Expert Syst. Appl.* **2011**, *38*, 14163–14168. [CrossRef]

83. Gupta, P.; Mehlawat, M.K.; Ahemad, F. Selection of Renewable Energy Sources: A Novel VIKOR Approach in an Intuitionistic Fuzzy Linguistic Environment. *Environ. Dev. Sustain.* **2022**, *25*, 3429–3467. [CrossRef]
84. Ecer, F.; Pamucar, D. MARCOS Technique under Intuitionistic Fuzzy Environment for Determining the COVID-19 Pandemic Performance of Insurance Companies in Terms of Healthcare Services. *Appl. Soft Comput.* **2021**, *104*, 107199. [CrossRef] [PubMed]
85. Schitea, D.; Deveci, M.; Iordache, M.; Bilgili, K.; Akyurt, İ.Z.; Iordache, I. Hydrogen Mobility Roll-up Site Selection Using Intuitionistic Fuzzy Sets Based WASPAS, COPRAS and EDAS. *Int. J. Hydrogen Energy* **2019**, *44*, 8585–8600. [CrossRef]
86. Raman, P. Online Shopping Characteristics and Their Influence on Female Buying Behavior: An Extension of the Theory of Planned Behavior. *J. Electron. Commer. Organ. JECO* **2020**, *18*, 1–29. [CrossRef]
87. Davidavičienė, V.; Tolvaišas, J. Measuring Quality of E-Commerce Web Sites: Case of Lithuania. *Econ. Manag.* **2011**, *16*, 723–729.
88. Lin, H.; Wu, X. Effect of Framing on Consumers' Willingness to Participate in a Promotion Campaign. *Soc. Behav. Personal. Int. J.* **2022**, *50*, 9. [CrossRef]
89. Akçagün, E.; Yılmaz, A.; Ceviz, N.Ö. The Effect of Covid-19 Pandemic on Consumer Shopping Habits: Case Study of University Students Covid 19 Pandemisinin Tüketici Alışveriş Alışkanlıklarına Etkisi: Üniversite Öğrencileri Örneği. *Istanb. Aydin. Üniv. Sos. Bilim. Derg.* **2021**, *14*, 179–197. [CrossRef]
90. Yilmaz, Z. Ranking Online Shopping Websites by Considering the Criteria Weights. *J. Bus. Res.* **2022**, *144*, 497–512. [CrossRef]
91. Martinovic, M.; Domovic, J.; Piric, V. Perception of Health Products and Trends in Online Shopping and Promotion of Health Products in Croatia. *Bull. Natl. Acad. Manag. Cult. Arts* **2018**, *1*, 1.
92. Ajripour, I. Applying MCDM Technique in Analyzing the Effect of Promotion Items Based on Online Shopping Factors: A Case Study. In Proceedings of the European Union's Contention in the Reshaping Global Economy, Szeged, Hungary, 20–21 May 2020; pp. 9–27.
93. Bae, Y.; Choi, J.; Gantumur, M.; Kim, N. Technology-Based Strategies for Online Secondhand Platforms Promoting Sustainable Retailing. *Sustainability* **2022**, *14*, 3259. [CrossRef]
94. Kurt, K.; Aktaş, B.; Turan, A. Understanding Online Shopping Continuance Intention of Turkish Users: An Empirical Assessment. *Pamukkale Univ. J. Soc. Sci. Inst.* **2021**, *50*, 144–160. [CrossRef]
95. Kim, J.; Jin, B.; Swinney, J.L. The Role of Etail Quality, e-Satisfaction and e-Trust in Online Loyalty Development Process. *J. Retail. Consum. Serv.* **2009**, *16*, 239–247. [CrossRef]
96. Ling, K.C.; Chai, L.T.; Piew, T.H. The Effects of Shopping Orientations, Online Trust and Prior Online Purchase Experience toward Customers' Online Purchase Intention. *Int. Bus. Res.* **2010**, *3*, 63. [CrossRef]
97. Uzir, M.U.H.; Al Halbusi, H.; Thurasamy, R.; Thiam Hock, R.L.; Aljaberi, M.A.; Hasan, N.; Hamid, M. The Effects of Service Quality, Perceived Value and Trust in Home Delivery Service Personnel on Customer Satisfaction: Evidence from a Developing Country. *J. Retail. Consum. Serv.* **2021**, *63*, 102721. [CrossRef]
98. Cui, G.; Lui, H.K.; Guo, X. The Effect of Online Consumer Reviews on New Product Sales. *Int. J. Electron. Commer.* **2012**, *17*, 39–58. [CrossRef]
99. Hong, D.H.; Choi, C.H. Multicriteria Fuzzy Decision-Making Problems Based on Vague Set Theory. *Fuzzy Sets Syst.* **2000**, *114*, 103–113. [CrossRef]
100. Chen, L.H.; Hung, C.C.; Tu, C.C. Considering the Decision Maker's Attitudinal Character to Solve Multi-Criteria Decision-Making Problems in an Intuitionistic Fuzzy Environment. *Knowl. Based Syst.* **2012**, *36*, 129–138. [CrossRef]
101. Szmidt, E.; Kacprzyk, J. Distances between Intuitionistic Fuzzy Sets. In *Fuzzy Sets and Systems*; Elsevier: Amsterdam, The Netherlands, 2000; Volume 114.
102. Xu, Z. Intuitionistic Fuzzy Aggregation Operators. *IEEE Trans. Fuzzy Syst.* **2007**, *15*, 1179–1187. [CrossRef]
103. Chawla, N.; Kumar, B. E-Commerce and Consumer Protection in India: The Emerging Trend. *J. Bus. Ethics* **2022**, *180*, 581–604. [CrossRef] [PubMed]
104. Fernández-Bonilla, F.; Gijón, C.; De la Vega, B. E-Commerce in Spain: Determining Factors and the Importance of the e-Trust. *Telecomm. Policy* **2022**, *46*, 102280. [CrossRef]
105. Lai, J.Y.; Ulhas, K.R.; Lin, J. Da Assessing and Managing E-Commerce Service Convenience. *Inf. Syst. Front.* **2014**, *16*, 273–289. [CrossRef]
106. Djafarova, E.; Rushworth, C. Exploring the Credibility of Online Celebrities' Instagram Profiles in Influencing the Purchase Decisions of Young Female Users. *Comput. Human Behav.* **2017**, *68*, 1–7. [CrossRef]
107. Raman, P. Understanding Female Consumers' Intention to Shop Online. *Asia Pac. J. Mark. Logist.* **2019**, *31*, 1138–1160. [CrossRef]
108. Zumstein, D.; Kotowski, W. *Success Factors of E-Commerce—Drivers of The Conversion Rate and Basket Value*; IADIS—International Association for the Development of the Information Society: Porto, Portugal, 2020; pp. 43–50.
109. Kinal, J. Peculiarities of E-Commerce Development: A Case of Poland. *Entrep. Sustain. Issues* **2022**, *9*, 50–63. [CrossRef] [PubMed]
110. Oga Laksana, M.; Elan Maulani, I.; Munawaroh, S. Development of E-Commerce Website Recommender System Using Collaborative Filtering and Deep Learning Techniques. *Devot. J. Community Serv.* **2023**, *4*, 636–641. [CrossRef]
111. Hannak, A.; Soeller, G.; Lazer, D.; Mislove, A.; Wilson, C. Measuring Price Discrimination and Steering on E-Commerce Web Sites. In Proceedings of the ACM SIGCOMM Internet Measurement Conference, IMC, Vancouver, BC, Canada, 5–7 November 2014; Association for Computing Machinery: New York, NY, USA, 2014; pp. 305–318.
112. Zhang, Y.; Abbas, H.; Sun, Y. Smart E-Commerce Integration with Recommender Systems. *Electron. Mark.* **2019**, *29*, 219–220. [CrossRef]

113. Purwandari, B.; Suriazdin, S.A.; Hidayanto, A.N.; Setiawan, S.; Phusavat, K.; Maulida, M. Factors Affecting Switching Intention from Cash on Delivery to E-Payment Services in C2C E-Commerce Transactions: COVID-19, Transaction, and Technology Perspectives. *Emerg. Sci. J.* **2022**, *6*, 136–150. [CrossRef]
114. Toprak Uçar, K.; Tümer, M.B.; Kıraç, M. Multi-Class Categorization of User-Generated Content in a Domain Specific Medium: Inferring Product Specifications from e-Commerce Marketplaces. In Proceedings of the Advances in Intelligent Systems and Computing; Springer Verlag: Berlin/Heidelberg, Germany, 2020; Volume 1029, pp. 247–256.
115. BDDK. Decision Nr: 8198. 2019; unpublished.
116. Pastijn, H.; Leysen, J. Constructing an Outranking Relation with ORESTE. In *Models and Methods in Multiple Criteria Decision Making*; Elsevier: Amsterdam, The Netherlands, 1989; Volume 12, pp. 1255–1268.
117. Retnowati, E.; Mardikaningsih, R. Study on Online Shopping Interest Based on Consumer Trust and Shopping Experience. *J. Mark. Bus. Res.* **2021**, *1*, 15–24.
118. Soleimani, M. Buyers' Trust and Mistrust in e-Commerce Platforms: A Synthesizing Literature Review. *Inf. Syst. e-Bus. Manag.* **2022**, *20*, 57–78. [CrossRef]
119. Zhang, C.; Ma, H.M. Introduction of the Marketplace Channel under Logistics Service Sharing in an E-Commerce Platform. *Comput. Ind. Eng.* **2022**, *163*, 107724. [CrossRef]
120. Chen, S.W.; Chen, P.H.; Tsai, C.T.; Liu, C.H. An Intelligent Based Symmetrical Classification of Online Shop Selling Counterfeit Products. *Symmetry* **2022**, *14*, 2132. [CrossRef]
121. Guo, F.; Ma, D.; Hu, J.; Zhang, L. Optimized Combination of E-Commerce Platform Sales Model and Blockchain Anti-Counterfeit Traceability Service Strategy. *IEEE Access* **2021**, *9*, 138082–138105. [CrossRef]
122. Fahmy, M.M.; Ragab, N.E. Enhancing Enterprise Competitiveness and Sustainability Using EWOM: The Case of Egypt. *Corp. Bus. Strategy Rev.* **2022**, *3*, 29–38. [CrossRef]
123. Sharma, G.; Wang, L. The Effects of Online Service Quality of E-Commerce Websites on User Satisfaction. *Electron. Libr.* **2015**, *33*, 468–485. [CrossRef]
124. Chen, J.V.; Yen, D.C.; Pornpriphet, W.; Widjaja, A.E. E-Commerce Web Site Loyalty: A Cross Cultural Comparison. *Inf. Syst. Front.* **2015**, *17*, 1283–1299. [CrossRef]
125. Subramanian, N.; Gunasekaran, A.; Yu, J.; Cheng, J.; Ning, K. Customer Satisfaction and Competitiveness in the Chinese E-Retailing: Structural Equation Modeling (SEM) Approach to Identify the Role of Quality Factors. *Expert Syst. Appl.* **2014**, *41*, 69–80. [CrossRef]
126. Svatosova, V. The Importance of Online Shopping Behavior in the Strategic Management of E-Commerce Competitiveness. *J. Compet.* **2020**, *12*, 143–160. [CrossRef]
127. Liu, X.; Tong, D.; Huang, J.; Zheng, W.; Kong, M.; Zhou, G. What Matters in the E-Commerce Era? Modelling and Mapping Shop Rents in Guangzhou, China. *Land Use Policy* **2022**, *123*, 106430. [CrossRef]
128. Karuppiah, K.; Sankaranarayanan, B.; Subramaniam, S. Evaluation of the Barriers in the Adoption of Automated Technology by the Manufacturing Sector: A Case from India. In *Advances in Materials and Mechanical Engineering*; Springer: Singapore, 2021; pp. 421–429.
129. Hussain, A.; Ullah, K.; Pamucar, D.; Haleemzai, I.; Tatić, D. Assessment of Solar Panel Using Multiattribute Decision-Making Approach Based on Intuitionistic Fuzzy Aczel Alsina Heronian Mean Operator. *Int. J. Intell. Syst.* **2023**, *2023*, 6268613. [CrossRef]
130. Karuppiah, K.; Sankaranarayanan, B.; Ali, S.M. A Novel Quality Function Deployment Based Integrated Framework for Improving Supply Chain Sustainability. *Eng. Manag. J.* **2022**, 1–14. [CrossRef]
131. Hussain, A.; Wang, H.; Ullah, K.; Garg, H.; Pamucar, D. Maclaurin symmetric mean aggregation operators based on novel Frank T-norm and T-conorm for intuitionistic fuzzy multiple attribute group decision-making. *Alex. Eng.J.* **2023**, *71*, 535–550. [CrossRef]