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AISAQUAL-Based Evaluation of AI-Supported E-Tourism Service Quality: An Interval-Valued q-Rung Orthopair Fuzzy Hamacher CIMAS Approach

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Abstract

With the increasing prevalence of AI-supported services, the assessment of service quality in the e-tourism sector has become a more complex and multidimensional process. This study aims to analyse the dimensions of AI-supported e-tourism service quality using an advanced fuzzy multi-criteria decision-making approach that takes into account uncertainty and hesitation in expert judgements. Within this scope, the relative importance levels of the criteria associated with the six fundamental dimensions defined within the AISAQUAL model were modelled using interval-valued q-rung orthopair fuzzy sets (IVq-ROFS), and a flexible and parametric integration process was applied via Hamacher operators. The analytical framework was structured using the CIMAS method, which directly reflects expert experience in the criterion weighting process; a multi-stage evaluation process was conducted by integrating decision-makers' levels of experience into the weighting mechanism. In this process, linguistic evaluations were converted into fuzzy numbers, combined using the Hamacher product operator, and reduced to precise values via scoring functions to calculate criterion weights. The findings indicate that incorporating uncertainty and interactions between criteria into the model leads to variations in the relative importance ranking of service quality dimensions. Furthermore, it was determined that the proposed approach produces more consistent and discriminatory results compared to classical weighting methods. In conclusion, the study demonstrates that the use of advanced fuzzy decision-making methods in the evaluation of AI-supported service quality can yield more realistic and reliable results.

Keywords: AISAQUAL; e-tourism service quality; interval-valued q-rung orthopair fuzzy sets (IVq-ROFS); CIMAS method

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1. Introduction

Complex decision-making problems are multidimensional structures that require the simultaneous evaluation of multiple and often conflicting criteria [1–3]. In the systematic analysis of such problems, multi-criteria decision-making (MCDM) methods play a significant role by providing decision-makers with a structured and analytical framework [4,5]. Especially in situations involving uncertainty, subjective evaluation, and multi-criteria structures, classical decision-making approaches prove inadequate, necessitating more advanced methods [6,7]. In this context, MCDM methods stand out as an effective tool for solving complex decision problems by enabling the holistic evaluation of diverse and often conflicting criteria [8–10].

With the acceleration of the digital transformation process, artificial intelligence (AI) technologies have brought about a profound transformation in the service sector, particularly in the tourism industry [11,12]. AI-based applications such as chatbots, recommendation systems, and virtual assistants stand out as systems capable of engaging in real-time interaction with users and restructuring service delivery through their learning capabilities [13,14]. These technologies enable the analysis of customer data, thereby contributing to more data-driven decision-making processes [15].

AI systems supported by big data analytics enable service providers to take proactive measures owing to their ability to predict user behaviour [16]. This necessitates a new perspective in service evaluations that focuses not only on outcomes but also on the service production process [17]. At the same time, the use of these systems brings elements such as data security and transparency to the forefront, making it necessary to consider new dimensions in the evaluation of service quality [18].

Furthermore, the nature of human–machine interaction directly influences how users perceive the service. Systems exhibiting human-like characteristics differentiate the user's interaction experience, leading to a reshaping of perceptions regarding service quality [19]. Therefore, AI-supported services should be evaluated not only in terms of technical performance but also in terms of the quality of the interaction established with the user. This transformation has necessitated a redefinition of the concept of service quality. While the traditional SERVQUAL model explains service quality through functional dimensions such as reliability, empathy, and responsiveness [20], the E-SERVQUAL approach developed for digital environments emphasizes technical elements such as system access, usability, information quality, and security [21,22]. However, AI-based service systems go beyond these two approaches, reshaping the very nature of service delivery [17,23,24]. These systems are not limited to merely providing information and performing transactions; they stand out as structures capable of interacting with users, learning, and generating context-sensitive responses [25–27].

AI-supported service environments introduce new evaluation dimensions such as personalization capacity, quality of interaction and the level of relationship established with the user, in addition to accuracy and operational efficiency [25,28]. Furthermore, the way in which users evaluate their service experience is based not only on functional benefits but also on factors such as perceived trust, emotional interaction and experiential satisfaction [26,29]. Therefore, AI-supported service quality should be approached as a multi-layered structure integrating cognitive, emotional and social elements, and evaluated beyond traditional measurement approaches [17,24].

In this context, the AISAQUAL model developed by Noor and colleagues structures AI-supported service quality across six dimensions: efficiency, security, availability, enjoyment, contact and anthropomorphism [17,30]. This framework demonstrates that service quality is not limited to technical performance indicators alone, but also encompasses the perceptual and interactive aspects of the user experience [22,23]. In particular, the nature of the interaction between the user and the system in AI-based services has become a decisive factor in the evaluation of service quality [26]. The dimensions included in the AISAQUAL model enable a more precise evaluation by distinguishing between the various components of service delivery. Whilst functional dimensions focus on system performance, experiential dimensions represent the factors that shape user perception [31–33]. This distinction allows AI systems to be analysed in terms of both operational efficiency and user-centred value creation [17]. In addition, perceptions of security and privacy play a critical role in users' adoption behaviour [18]. The communication dimension, meanwhile, determines the continuity of interaction between the user and the system, thereby enabling a holistic evaluation of the service experience [29]. In this respect, the AISAQUAL model offers a significant methodological contribution to the existing literature by addressing AI-supported service quality within a multidimensional and analytical framework. Anthropomorphism transforms the nature of interaction by leading users to perceive AI systems as social entities rather than merely functional tools [26,32]. This situation increases the perceived closeness between the user and the system and reinforces parasocial interaction mechanisms [19]. On the other hand, data privacy and the perception of system reliability are among the key determinants of users' trust in the platform [18]. Hedonic value, meanwhile, represents the emotional dimension of the digital service experience and emerges as a key factor supporting user satisfaction and the intention to reuse the service [28].

Whilst the existing literature presents significant advances regarding AI-supported service quality, it indicates that studies addressing the multidimensional components of this framework in a holistic manner remain limited [34–36]. In particular, the majority of studies in the literature focus on techniques such as scale development and structural equation modelling aimed at measuring user perceptions; this situation leads to insufficient analysis of the interplay between criteria and their relative levels of importance [34,37]. This trend indicates that the multi-criteria decision-making perspective has been integrated only to a limited extent in service quality assessments [4,10]. Furthermore, the modelling of uncertainty and indecision arising in expert-based evaluations is often overlooked in classical statistical approaches [38,39]. Consequently, there is a need for advanced decision-making approaches that address uncertainty and inter-criterion relationships together in order to analyse AI-supported service quality more realistically [40].

Unlike existing fuzzy MCDM studies that generally employ classical fuzzy, intuitionistic fuzzy, or spherical fuzzy environments separately, this study proposes an integrated IVq-ROF-Hamacher-CIMAS framework for evaluating AI-supported e-tourism service quality. The proposed approach simultaneously incorporates interval-valued uncertainty, q-rung orthopair membership structures, and flexible Hamacher aggregation operators within the CIMAS weighting mechanism. In this respect, the study extends existing AISAQUAL-based evaluations by providing a more flexible and uncertainty-sensitive decision-making structure. Furthermore, while previous studies mainly focus on conventional service quality assessment models, this research specifically adapts the framework to AI-supported e-tourism services and prioritizes AISAQUAL dimensions under uncertain expert evaluations. Therefore, the study contributes to the literature both methodologically and contextually.

In the analysis of structures involving multidimensional and subjective assessments, such as AI-supported service quality, the explicit modelling of uncertainty is of critical importance [7,38]. In this context, fuzzy logic-based approaches make decision-makers' linguistic and non-precise judgements quantifiable and analysable, thereby producing more realistic results in multi-criteria decision-making processes [6,41]. In particular, q-rung orthopair fuzzy sets provide greater flexibility compared to classical fuzzy and intuitive fuzzy structures, as they can express membership and non-membership degrees across a broader solution space [42]. The interval-valued form of this structure, meanwhile, enhances the reliability of the evaluation process by representing decision-makers' levels of uncertainty more comprehensively [43]. Consequently, the interval-valued q-rung orthopair fuzzy Hamacher operator-based approach employed in this study provides a suitable methodological framework for evaluating the multidimensional structure of AI-supported service quality in a more consistent and analytical manner.

This study aims to fill the aforementioned theoretical and methodological gap. In this context, the CIMAS method, based on the Interval-Valued q-Rung Orthopair Fuzzy

Hamacher operator, is applied to determine the relative importance of the dimensions of AI-supported e-tourism service quality. The CIMAS method was selected because it enables the determination of the importance levels of criteria within a systematic and comparative framework and due to its consistency-oriented structure. Furthermore, by offering a more flexible evaluation process compared to classical weighting methods, it ensures that decision-makers' judgements are reflected in a more balanced manner [5,10]. Within this framework, the q-rung orthopair fuzzy approach models uncertainty across a broader solution space, thereby representing decision-makers' levels of hesitation more effectively [42]. Interval-valued extension enhances the model's sensitivity by accounting for the uncertainty range in evaluations [43]. Hamacher operators, meanwhile, strengthen the consistency of results by enabling the parametric and flexible integration of evaluation data [44,45]. This integrated approach enables a more precise and analytical assessment of the multidimensional structure of AI-supported service quality. In this respect, the study fills a methodological gap in the literature by addressing the AISAQUAL dimensions within a fuzzy multi-criteria decision-making framework, thereby offering a unique and comprehensive contribution to both AI-supported service quality research and the MCDM literature.

The selection of this approach is based on three main reasons. First, the AISAQUAL framework includes multidimensional and perception-based criteria such as efficiency, security, availability, enjoyment, contact, and anthropomorphism, which require expert-based evaluation under uncertainty. Therefore, a fuzzy MCDM approach is more appropriate than classical weighting techniques. Second, interval-valued q-rung orthopair fuzzy sets were preferred because they allow membership and non-membership degrees to be represented within interval values, thereby capturing hesitation, ambiguity, and conflicting expert judgements more comprehensively. Third, the CIMAS method was selected because it provides a systematic and consistency-oriented criterion weighting procedure while incorporating the experience levels of decision-makers into the weighting mechanism. This is especially relevant for expert-based service quality assessment, where the knowledge and professional background of decision-makers may directly influence the reliability of evaluations.

Compared with commonly used MCDM methods, the proposed approach does not merely rank criteria but also supports a structured weighting process that reduces subjectivity and reflects expert competence. In addition, Hamacher operators provide a flexible parametric aggregation structure, which strengthens the integration of fuzzy evaluations. Accordingly, the selected approach was considered more suitable for the purpose of this study than conventional MCDM methods, because it simultaneously addresses uncertainty, expert hesitation, experience-based weighting, and consistency in the evaluation process.

In this context, the study aims to analyse the multidimensional structure of AI-supported e-tourism service quality within a holistic framework. Within this scope, the study focuses on the following three main research questions:

1. RQ1: What are the relative importance levels of the AISAQUAL dimensions that constitute AI-supported e-tourism service quality?
2. RQ2: How does the CIMAS method, based on the interval-valued q-rung orthopair fuzzy Hamacher operator, provide analytical differentiation in the weighting of these dimensions?
3. RQ3: How does the inclusion of uncertainty and interactions between criteria in the model affect the results of AI-supported service quality evaluation?

In this context, the study aims to make a methodological contribution to both the literature on AI-supported service quality and fuzzy multi-criteria decision-making approaches.

The remainder of the study is structured as follows: the next section presents a comprehensive literature review on the subject to establish the theoretical framework. Subsequently, the methodology is explained in detail, and the application process of the CIMAS approach, based on the interval-valued q-rung orthopair fuzzy Hamacher operator, is outlined. The findings are then presented and analysed. In the final section, the findings are discussed, theoretical and practical implications are evaluated, and recommendations for future research are provided.

2. Literature Review

2.1. The Concept of Artificial Intelligence-Supported Service Quality (AI-SQ)

With the increasing pace of the digitalization process, the integration of AI technologies into the service industry has dramatically changed the customer–business relationship [11,17]. In particular, the implementation of AI-based systems on online tourism websites has the capacity to offer services customized to the users' preferences [46]. For this purpose, online AI tools including chatbots, recommendation engines, virtual agents and customized booking algorithms are reshaping the service logic, offering operational assistance to the customers at all times [13,19].

With the acceleration of the digitalization process, the use of artificial intelligence (AI) technologies in the service sectors has fundamentally transformed the way businesses interact with customers [11,17]. AI-based systems used in online tourism websites have the potential to provide services tailored to users' needs [46]. Tools such as chatbots, recommendation engines, virtual assistants and personalized booking algorithms are reshaping the service experience by providing users with seamless support [13,19]. Recent studies indicate that these systems not only enhance operational efficiency but also make the user experience more dynamic and context-sensitive [47,48].

AI-enabled service quality represents a framework that goes beyond the traditional understanding of service quality by integrating the cognitive, emotional and behavioural dimensions of human–machine interaction [17,31]. Developed within this framework, the AISAQUAL scale has become a key reference point for measuring AI-enabled service quality across six dimensions: efficiency, safety, accessibility, enjoyment, communication and anthropomorphism [30]. These dimensions offer a more holistic assessment by expanding the technical-focused approach of the traditional E-SERVQUAL model to encompass the perceptual and interactive aspects of the user experience [22,23].

The importance of AI-powered systems in the context of tourism websites can be explained by their ability to enhance both the ease of access to information and the quality of interaction for customers. AI-based recommendation systems and data analytics applications enable the delivery of personalized services by analysing user behaviour and optimizing decision-making processes [16,48]. At the same time, automated customer support systems enhance user satisfaction by providing high availability and strengthening service continuity [29]. Recent findings indicate that the impact of AI-supported service quality on customer satisfaction, trust and loyalty is becoming increasingly evident [36,49].

2.2. The Dimensions of AI-Enabled Service Quality

AI-enabled service quality comprises six key dimensions: efficiency, security, accessibility, enjoyment, communication and anthropomorphism. The specific meaning of each dimension within the context of artificial intelligence and its theoretical foundations are discussed below.

2.2.1. Efficiency

The efficiency dimension refers to AISA's capacity to meet user needs quickly, accurately and with minimal effort. Whilst in traditional service quality literature, efficiency is associated with the dimensions of service speed and ease of use, within the context of AI-supported services, this concept is evolving into a more sophisticated framework [17,22]. Artificial intelligence systems can analyse user behaviour through big data analytics and machine learning algorithms to provide personalized and optimized solutions [34,47]. This not only increases the speed of service delivery but also enhances its accuracy and contextual appropriateness. In this context, efficiency is not limited solely to processing time; it is also associated with a reduction in cognitive load, the acceleration of the decision-making process, and the user experience approaching a state of flow [28,37]. The recommendation mechanisms and decision-support tools offered by AI-enabled systems enable faster and more reliable decision-making processes by reducing uncertainty [19]. Furthermore, reducing the complexity arising during the information access process and simplifying user interaction directly increases perceived service efficiency [29]. When evaluated within the technology acceptance model (TAM), the variables of perceived ease of use and perceived usefulness are among the key theoretical determinants of AISA effectiveness [50,51]. These variables directly influence users' intention to adopt and continue using the system, thereby shaping the perceived level of service quality [52]. Recent studies indicate that the impact of the efficiency dimension in AI-supported services on user satisfaction, trust and loyalty is becoming increasingly evident [36,49].

In this context, efficiency, as one of the fundamental building blocks of AI-supported service quality, offers a multi-layered evaluation framework that encompasses not only technical performance but also the cognitive and behavioural dimensions of the user experience. In this respect, the efficiency dimension is regarded as a critical criterion that should be prioritized in multi-criteria decision-making models.

2.2.2. Security

The security dimension encompasses users' perceptions regarding the protection of their personal data and the reliability of the system during their interaction with AISA. Given the data-intensive nature of artificial intelligence systems, security is considered not merely a technical element, but also a perceptual and psychological factor [18,53]. This dimension includes sub-elements such as perceived risk, data privacy, transparency, ethical use and system integrity [54,55]. In particular, users' ability to access clear and understandable information regarding how their personal data is collected, processed and stored significantly enhances their perception of trust [18].

Trust in AI-based services is closely linked to the system's accuracy, consistency and predictability; these characteristics directly influence users' acceptance of and intention to use the technology [19,31]. Furthermore, algorithmic transparency and explainability enhance perceived trust by enabling users to understand how system outputs are generated [47]. In this context, the security dimension encompasses not only data protection mechanisms but also the establishment of a trust relationship between the user and the system. Within the framework of Privacy Calculus Theory, users weigh the benefits they will gain against the risks of data sharing and decide on technology use accordingly [54]. This balance becomes particularly pronounced in AI systems offering personalized services; as perceived benefit increases, willingness to share data rises [18,56]. Consequently, security emerges as a critical factor determining not only usage intent but also user satisfaction, loyalty and long-term system usage [36,49].

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2.2.3. Accessibility

Accessibility refers to AISA being easily accessible to users at any time and from anywhere. Whilst time and location constraints are significant limiting factors in traditional services, AI-based services largely eliminate these limitations through their capacity to provide uninterrupted 24/7 service [17,22]. This transformation enhances the continuity of service access, enabling users to interact with the system whenever they need to [29]. In the context of AISA, accessibility is directly linked to multi-platform support (mobile, web and IoT-based systems), rapid access, system continuity and user-friendly interfaces [46,47]. In particular, cloud-based infrastructures and distributed system architectures enhance accessibility by enabling services to be delivered seamlessly across different devices. Furthermore, the ability to deliver services even under low-bandwidth conditions, compatibility with different devices, and the continuity of the user experience constitute the technical dimensions of accessibility [34].

Another key aspect of the accessibility dimension is its relationship with social inclusion. Different language options, cultural adaptation, and accessibility solutions developed for people with disabilities (such as voice command systems and screen reader compatibility) ensure that digital services reach a wider user base [53,57]. In this context, accessibility is not merely a technical feature; it is regarded as a multidimensional structure that must be addressed from the perspectives of service equity and digital inclusion [58]. Recent studies have shown that the level of accessibility has a direct impact on user satisfaction, system usage and intention to reuse [36,47]. In this context, accessibility is a critical factor for the sustainability of AI-supported service quality and stands out as one of the key components ensuring the continuity of the user experience.

2.2.4. Enjoyment

The enjoyment dimension refers to the fact that the use of AISA offers not only a functional but also a hedonic experience. Whilst this dimension is often overlooked in traditional service quality studies, it has become a key differentiating factor in digital and AI-based services [17,28]. In particular, as the user experience becomes increasingly interactive and personalized, the importance of emotional and hedonic factors in service evaluations is growing [47].

AISA systems incorporate gamification elements, interactive interface designs and personalization mechanisms that respond to user preferences, with the aim of making user interaction more engaging. Such applications encourage users to engage with the system for longer periods, thereby increasing the perceived value of the experience [37,59]. In this context, enjoyment is directly linked to the pleasure, satisfaction and emotional fulfilment users derive from the service, and represents the emotional dimension of the user experience [28].

Furthermore, the curiosity, sense of discovery and perception of novelty experienced by users whilst interacting with the system are also factors that reinforce the enjoyment dimension. Innovative AI applications enhance experiential value by making users' interaction with the service more dynamic and engaging [19,47]. This enables users to engage not only in a task-oriented manner but also in an experience-oriented one. When evaluated within the framework of Flow Theory, users lose their sense of time whilst interacting with AISA, focusing entirely on the experience, and demonstrating a high level of cognitive–behavioural engagement represents the highest level of the enjoyment dimension [60,61]. Such experiences not only enhance user satisfaction but also exert a powerful influence on the intention to reuse and loyalty [36].

Consequently, the enjoyment dimension is regarded as a critical element in enhancing experience quality, particularly within the context of tourism and recreation; it demonstrates that AI-supported service quality constitutes a multi-layered structure encompassing not only performance but also emotional and experiential value dimensions.

2.2.5. Communication

The communication dimension refers to the quality of the interaction established by AISA with users. This dimension encompasses not only the transfer of information but also the capacity to engage in meaningful, contextual and fluent dialogue [17,26]. The natural language processing (NLP) and natural language generation (NLG) capabilities of artificial intelligence systems enable the generation of appropriate and consistent responses by accurately interpreting user intent and are therefore among the key determinants of communication quality [47].

Communication quality encompasses elements such as response accuracy, speed, contextual awareness, personalization, and the ability to provide empathetic responses. These elements directly influence the naturalness and continuity of the interaction users establish with the system [29]. Contextual awareness and personalization enhance perceived service quality by ensuring content is delivered in line with users' expectations [19]. Furthermore, features such as the ability to communicate in multiple languages, generate responses appropriate to the cultural context, and adapt to different user profiles are of critical importance for systems providing services on a global scale [46].

This dimension demonstrates that AISA is perceived not merely as a technical tool, but also as a social actor. Systems with a high level of social presence contribute to users perceiving their interaction experience as more human-like and natural [26]. Within the framework of Social Presence Theory, it is observed that users evaluate systems that offer warmer, more empathetic and interactive communication as more reliable and of higher quality [62,63]. Similarly, Media Richness Theory demonstrates that the effectiveness of information transfer increases with the richness of the communication channel, and that systems offering richer communication possess higher perceived quality [64]. Recent studies indicate that the quality of AI-supported communication has a direct impact on user satisfaction, trust and intention to reuse [36,47]. In this context, the communication dimension plays a critical role in the success of AISA systems and emerges as one of the key components shaping the social and interactive dimensions of the user experience.

2.2.6. Anthropomorphism

Anthropomorphism refers to the extent to which an AISA exhibits human-like characteristics. This dimension relates to the capacity of artificial intelligence systems to speak like humans, express emotions, produce gestures and facial expressions, and engage in social interaction [26,65]. In digital service environments, anthropomorphic design elements contribute to users perceiving the system as more 'human-like' and approachable, thereby enhancing the quality of interaction [17,31]. Anthropomorphism helps users establish a stronger connection with technology, enhances the perception of social presence, and makes interactions with the system feel more natural [63]. According to the CASA (computers are social actors) approach, individuals apply social norms and behavioural patterns directed towards humans in their interactions with technology; this leads to artificial intelligence systems being perceived as social actors [66]. Within this framework, anthropomorphic features positively influence the quality of the service experience by increasing users' levels of trust, satisfaction and loyalty [19,47]. However, the excessive use of anthropomorphism can lead to a phenomenon known as the 'uncanny valley', which causes a sense of unease in the user [67]. When human likeness exceeds a certain threshold, users may perceive the system as artificial and unsettling rather than natural. For this reason, anthropomorphism is regarded as a critical dimension in AISA design that must be carefully balanced, as it presents both opportunities and risks [31]. Recent studies indicate that anthropomorphic features have significant effects on user trust, interaction duration, brand loyalty and quality of experience [36,47]. In this context, anthropomorphism emerges as one of the key elements shaping the social and emotional dimensions of AI-supported service quality, presenting a significant area for future research.

In this context, anthropomorphism emerges as a critical factor that transforms the interaction experience by leading users to perceive AI systems as social entities rather than merely functional tools [26,31]. Furthermore, data privacy and system reliability rank among the key determinants of users' trust in the platform; hedonic value, meanwhile, represents the emotional dimension of the experience, thereby reinforcing satisfaction and the intention to reuse [18,28]. For this reason, AI-SQ should not be viewed merely as a concept focused on technological performance; rather, it should be regarded as a multi-layered structure that addresses the technical, emotional and social dimensions of the user experience collectively.

Although studies on AI-SQ have been conducted and reported in the literature, it is evident that there are few studies that systematically analyse this multidimensional construct in terms of inter-criterion relationships and relative importance [34–36]. In particular, the majority of existing studies rely on survey-based statistical methods and fail to adequately model uncertainty and decision-maker hesitation [37,39]. This situation highlights the importance of fuzzy logic-based multi-criteria decision-making approaches for a more realistic analysis of AI-supported service quality [6,7]. In this context, q-rung orthopair fuzzy and interval-valued fuzzy structures enable decision-makers' evaluations to be represented more accurately by modelling uncertainty within a broader solution space [42,43]. Hamacher operators, on the other hand, enhance the consistency of analysis results by enabling the flexible integration of fuzzy information [44,45]. In light of these developments, the use of advanced fuzzy multi-criteria decision-making approaches to analyse the multidimensional structure of AI-supported service quality offers a methodologically robust alternative. This study focuses on prioritizing AI-supported e-tourism service quality criteria under uncertainty through an integrated IVq-ROF Hamacher CIMAS approach.

Previous fuzzy MCDM studies have provided important contributions to service quality evaluation and complex decision-making problems [4,10]. However, several methodological limitations still remain in the literature. Many existing studies generally employ classical fuzzy, intuitionistic fuzzy, Pythagorean fuzzy, or spherical fuzzy environments separately [38,42], which limits the representation of hesitation and interval-based uncertainty in expert evaluations. Furthermore, previous approaches mainly focus on ranking or weighting criteria, while decision-maker experience and the consistency of group evaluations are often not sufficiently incorporated into the analysis process. Another important limitation is that AI-supported service quality has mostly been evaluated through statistical approaches or traditional service quality frameworks rather than uncertainty-sensitive fuzzy MCDM models [17,30]. In this respect, the proposed IVq-ROF-Hamacher-CIMAS framework aims to overcome these limitations by integrating interval-valued q-rung orthopair fuzzy sets, Hamacher aggregation operators, and the CIMAS weighting mechanism within a single analytical structure. Therefore, the proposed approach provides a more flexible, uncertainty-sensitive, and experience-oriented framework for prioritizing AISAQUAL criteria in AI-supported e-tourism services.

3. Materials and Methods

The methodology section consists of preliminaries related to q-rung orthopair fuzzy sets (q-ROFSs), interval valued q-rung orthopair fuzzy sets (IVq-ROFSs), Hamacher operations related to IVq-ROFSs, and the IVq-ROF-Hamacher-CIMAS approach.

3.1. Preliminaries Related to q-ROFSs

Assume $B = \{b_1, b_2, \ldots, b_n\}$ as a nonempty fixed set. A q-ROFS E on B is defined according to Yager (2017) [42] as below:

$$E = \{\langle b_i, \mu_E(b_i), v_E(b_i)\rangle | b_i \in B\} \tag{1}$$

where $\mu_E(b_i)$ and $v_E(b_i)$ show the membership and non-membership degree related to the element $b_i \in B$ on q-ROFS E respectively, and $0 \leq \mu_E(b_i), v_E(b_i) \leq 1$ satisfying the condition of $0 \leq (\mu_E(b_i))^q + (v_E(b_i))^q \leq 1$, where $q \geq 1$.

The hesitancy degree related to $b_i \in B$ for q-ROFS E is denoted as follows:

$$HD_E(b_i) = \sqrt[q]{1 - (\mu_E(b_i))^q - (v_E(b_i))^q} \tag{2}$$

where $0 \leq HD_E(b_i) \leq 1$. A q-rung orthopair fuzzy number (q-ROFN) shown as $\langle \mu_E(b), v_E(b)\rangle$ according to Yager (2017) [42]. For simplicity a q-ROFN can be denoted as $E = \langle \mu_E, v_E\rangle$.

Assume $E = (\mu_E, v_E)$, $E_1 = (\mu_{E_1}, v_{E_1})$ and $E_2 = (\mu_{E_2}, v_{E_2})$ as three q-ROFNs and $\lambda > 0$. Related operational laws are determined as below [42,45]:

$$E_1 \cap E_2 = \langle min\{\mu_{E_1}, \mu_{E_2}\}, max\{v_{E_1}, v_{E_2}\}\rangle \tag{3}$$

$$E_1 \cup E_2 = \langle max\{\mu_{E_1}, \mu_{E_2}\}, min\{v_{E_1}, v_{E_2}\}\rangle \tag{4}$$

$$E_1 \bigoplus E_2 = \langle \sqrt[q]{\mu_{E_1}^q + \mu_{E_2}^q - \mu_{E_1}^q \mu_{E_2}^q},\ v_{E_1} v_{E_2}\rangle \tag{5}$$

$$E_1 \bigotimes E_2 = \langle \mu_{E_1}\mu_{E_2}, \sqrt[q]{v_{E_1}^q + v_{E_2}^q - v_{E_1}^q v_{E_2}^q}\rangle \tag{6}$$

$$\lambda.E = \langle \sqrt[q]{1 - \left(1 - \mu_E^q\right)^\lambda}, v_E^\lambda\rangle \tag{7}$$

$$E^\lambda = \langle \mu_E^\lambda, \sqrt[q]{1 - \left(1 - v_E^q\right)^\lambda}\rangle \tag{8}$$

Let $E = (\mu_E, v_E)$ be a q-ROFN, and then score $Sc(E)$ and accuracy $Ac(E)$ functions are obtained as given below [42]:

$$Sc(E) = \mu_E^q - v_E^q,\ S(E) \in [-1, 1] \tag{9}$$

$$Ac(E) = \mu_E^q + v_E^q \tag{10}$$

Assume $E_i = (\mu_{E_i}, v_{E_i})$ $(i = 1, 2, \ldots, n)$ and $w = (w_1, w_2, \ldots, w_n)^T$ as a weight vector for E_i with $\sum_{i=1}^n w_i = 1$ and $w_i \in [0, 1]$. Q-rung orthopair fuzzy weighted average (q-ROFWA) and geometric (q-ROFWG) operators are determined according to Liu and Wang (2017) [45] as follows:

$$q - ROFWA = \left(\sqrt[q]{\left(1 - \prod_{i=1}^n \left(1 - \mu_{E_i}^q\right)^{w_i}\right)}, \prod_{i=1}^n v_{E_i}^{w_i}\right) \tag{11}$$

$$q - ROFWG = \left(\prod_{i=1}^n \mu_{E_i}^{w_i}, \sqrt[q]{\left(1 - \prod_{i=1}^n \left(1 - v_{E_i}^q\right)^{w_i}\right)}\right) \tag{12}$$

3.2. Preliminaries for IVq-ROFSs

Assume $B = \{b_1, b_2, \ldots, b_n\}$ as a nonempty fixed set. An IVq-ROFS E on B is determined as indicated below [43]:

$$\mathrm{E} = \left\{ \langle b, \left[\mu_E^{Lw}(b), \mu_E^{Up}(b)\right], \left[\vartheta_E^{Lw}(b), \vartheta_E^{Up}(b)\right] \rangle | b\epsilon B \right\} \tag{13}$$

The membership and non-membership degrees related to the component $b\epsilon B$ are shown via $\left[\mu_E^{Lw}(b), \mu_E^{Up}(b)\right]$ and $\left[\vartheta_E^{Lw}(b), \vartheta_E^{Up}(b)\right]$, respectively. For every $b\epsilon B$, $\left[\mu_E^{Lw}(b), \mu_E^{Up}(b)\right] \in [0,1]$ and $\left[\vartheta_E^{Lw}(b), \vartheta_E^{Up}(b)\right] \in [0,1]$ satisfy the condition of $\mu_E^{Up}(b)^q + \vartheta_E^{Up}(b)^q \leq 1$ where $q \geq 1$.

The hesitancy degree related to $b_i \in B$ for IVq-ROFS E is obtained as follows:

$$HD_E(b_i) = \left[\pi_E^{Lw}(b), \pi_E^{Up}(b)\right] = \left[\sqrt[q]{1 - \left(\mu_E^{Up}(b)\right)^q - \left(\vartheta_E^{Up}(b)\right)^q}, \sqrt[q]{1 - (\mu_E^{Lw}(b))^q - (\vartheta_E^{Lw}(b))^q}\right] \tag{14}$$

For simplicity an interval valued q-rung orthopair fuzzy number (IVq-ROFN) is shown as $E = \langle \left[\mu_E^{Lw}, \mu_E^{Up}\right], \left[\vartheta_E^{Lw}, \vartheta_E^{Up}\right] \rangle$.

Assume $E = \langle (\mu^{Lw}, \mu^{Up}), (\vartheta^{Lw}, \vartheta^{Up}) \rangle$, $E_1 = \langle \left(\mu_1^{Lw}, \mu_1^{Up}\right), \left(\vartheta_1^{Lw}, \vartheta_1^{Up}\right) \rangle$ and $E_2 = \langle \left(\mu_2^{Lw}, \mu_2^{Up}\right), \left(\vartheta_2^{Lw}, \vartheta_2^{Up}\right) \rangle$ as three IVq-ROFNs and $\lambda > 0$. Related operational laws are determined as given below [43]:

$$\begin{aligned} E_1 \bigoplus E_2 = &\left[\sqrt[q]{(\mu_1^{Lw})^q + (\mu_2^{Lw})^q - (\mu_1^{Lw})^q (\mu_2^{Lw})^q}, \sqrt[q]{\left(\mu_1^{Up}\right)^q + \left(\mu_2^{Up}\right)^q - \left(\mu_1^{Up}\right)^q \left(\mu_2^{Up}\right)^q}\right], \\ &\left[\vartheta_1^{Lw}\vartheta_2^{Lw}, \vartheta_1^{Up}\vartheta_2^{Up}\right] \end{aligned} \tag{15}$$

$$E_1 \bigotimes E_2 = \left[\mu_1^{Lw}\mu_2^{Lw}, \mu_1^{Up}\mu_2^{Up}\right], \left[\begin{array}{c} \sqrt[q]{(\vartheta_1^{Lw})^q + (\vartheta_2^{Lw})^q - (\vartheta_1^{Lw})^q (\vartheta_2^{Lw})^q}, \\ \sqrt[q]{\left(\vartheta_1^{Up}\right)^q + \left(\vartheta_2^{Up}\right)^q - \left(\vartheta_1^{Up}\right)^q \left(\vartheta_2^{Up}\right)^q} \end{array}\right] \tag{16}$$

$$\lambda.E = \left[\sqrt[q]{(1 - (1 - \mu^{Lw})^q)^\lambda}, \sqrt[q]{\left(1 - (1 - \mu^{Up})^q\right)^\lambda}\right], \left[\left(\vartheta^{Lw}\right)^\lambda, \left(\vartheta^{Up}\right)^\lambda\right] \tag{17}$$

$$E^\lambda = \left[\left(\mu^{Lw}\right)^\lambda, \left(\mu^{Up}\right)^\lambda\right], \left[\sqrt[q]{(1 - (1 - \vartheta^{Lw})^q)^\lambda}, \sqrt[q]{\left(1 - (1 - \vartheta^{Up})^q\right)^\lambda}\right] \tag{18}$$

Assume $E = \left(\mu^{Lw}, \mu^{Up}\right), \left(\vartheta^{Lw}, \vartheta^{Up}\right)$ as an IVq-ROFN, then score $Sc(E)$ and accuracy $Ac(E)$ functions are acquired as shown below [43]:

$$Sc(E) = \frac{1}{4}\left[1 + \left(\mu_E^{Lw}\right)^q - \left(\vartheta_E^{Lw}\right)^q + 1 + \left(\mu_E^{Up}\right)^q - \left(\vartheta_E^{Up}\right)^q\right], 0 \leq Sc(E) \leq 1 \tag{19}$$

$$Ac(E) = \frac{1}{2}\left[\left(\mu_E^{Lw}\right)^q + \left(\mu_E^{Up}\right)^q + \left(\vartheta_E^{Lw}\right)^q + \left(\vartheta_E^{Up}\right)^q\right], 0 \leq Ac(E) \leq 1 \tag{20}$$

3.3. Hamacher Operations Related to IVq-ROFSs

Assume $E_q(b_i) = \langle \left[\mu_{E_q}^{Lw}(b_i), \mu_{E_q}^{Up}(b_i)\right], \left[\vartheta_{E_q}^{Lw}(b_i), \vartheta_{E_q}^{Up}(b_i)\right] \rangle; i = 1, 2, \ldots, n$ and $F_q(b_i) = \langle \left[\mu_{F_q}^{Lw}(b_i), \mu_{F_q}^{Up}(b_i)\right], \left[\vartheta_{F_q}^{Lw}(b_i), \vartheta_{F_q}^{Up}(b_i)\right] \rangle; i = 1, 2, \ldots, n$ as two IVq-ROFNs that is described on the B universe of discourse $b_i \in B$. For simplicity in terms of computation these IVq-ROFNs can be written as indicated below:

$E_q(b_i) = \langle [o_E(b_i), p_E(b_i)], [r_E(b_i), s_E(b_i)] \rangle_q; \quad \forall i = 1, 2, \ldots, n$ and $F_q(b_i) = \langle [o_F(b_i), p_F(b_i)], [r_F(b_i), s_F(b_i)] \rangle_q$; $\forall i = 1, 2, \ldots, n$ and $q \geq 1$. Following to that, related operational laws including Hamacher addition, multiplication, scalar multiplication and scalar power are determined as given below [43]

$$\forall i: E_q(b_i) \bigoplus\nolimits_{Hmc_\lambda} F_q(b_i) = \left\langle \begin{array}{c} \left[\begin{array}{c} \sqrt[q]{\left(\frac{o_E^q(b_i)+o_F^q(b_i)-o_E^q(b_i)o_F^q(b_i)-(1-\lambda)o_E^q(b_i)o_F^q(b_i)}{1-(1-\lambda)o_E^q(b_i)o_F^q(b_i)} \right)}, \\ \sqrt[q]{\left(\frac{p_E^q(b_i)+p_F^q(b_i)-p_E^q(b_i)p_F^q(b_i)-(1-\lambda)p_E^q(b_i)p_F^q(b_i)}{1-(1-\lambda)p_E^q(b_i)p_F^q(b_i)} \right)} \end{array} \right], \\ \left[\begin{array}{c} \sqrt[q]{\left(\frac{r_E^q(b_i)r_F^q(b_i)}{\lambda+(1-\lambda)\left(r_E^q(b_i)+r_F^q(b_i)-r_E^q(b_i)r_F^q(b_i)\right)} \right)}, \\ \sqrt[q]{\left(\frac{s_E^q(b_i)s_F^q(b_i)}{\lambda+(1-\lambda)\left(s_E^q(b_i)+s_F^q(b_i)-s_E^q(b_i)s_F^q(b_i)\right)} \right)} \end{array} \right] \end{array} \right\rangle \tag{21}$$

$$\forall i: E_q(b_i) \bigotimes\nolimits_{Hmc_\lambda} F_q(b_i) = \left\langle \begin{array}{c} \left[\begin{array}{c} \sqrt[q]{\left(\frac{o_E^q(b_i)o_F^q(b_i)}{\lambda+(1-\lambda)\left(o_E^q(b_i)+o_F^q(b_i)-o_E^q(b_i)o_F^q(b_i)\right)} \right)}, \\ \sqrt[q]{\left(\frac{p_E^q(b_i)p_F^q(b_i)}{\lambda+(1-\lambda)\left(p_E^q(b_i)+p_F^q(b_i)-p_E^q(b_i)p_F^q(b_i)\right)} \right)} \end{array} \right], \\ \left[\begin{array}{c} \sqrt[q]{\left(\frac{r_E^q(b_i)+r_F^q(b_i)-r_E^q(b_i)r_F^q(b_i)-(1-\lambda)r_E^q(b_i)r_F^q(b_i)}{1-(1-\lambda)r_E^q(b_i)r_F^q(b_i)} \right)}, \\ \sqrt[q]{\left(\frac{s_E^q(b_i)+s_F^q(b_i)-s_E^q(b_i)s_F^q(b_i)-(1-\lambda)s_E^q(b_i)s_F^q(b_i)}{1-(1-\lambda)s_E^q(b_i)s_F^q(b_i)} \right)} \end{array} \right] \end{array} \right\rangle \tag{22}$$

$$\forall i: \beta \bigotimes\nolimits_{Hmc_\lambda} E_q(b_i) = \left\langle \begin{array}{c} \left[\begin{array}{c} \sqrt[q]{\left(\frac{\left(1-(1-\lambda)o_E^q(b_i)\right)^\beta-\left(1-o_E^q(b_i)\right)^\beta}{\left(1-(1-\lambda)o_E^q(b_i)\right)^\beta-(1-\lambda)\left(1-o_E^q(b_i)\right)^\beta} \right)}, \\ \sqrt[q]{\left(\frac{\left(1-(1-\lambda)p_E^q(b_i)\right)^\beta-\left(1-p_E^q(b_i)\right)^\beta}{\left(1-(1-\lambda)p_E^q(b_i)\right)^\beta-(1-\lambda)\left(1-p_E^q(b_i)\right)^\beta} \right)} \end{array} \right], \\ \left[\begin{array}{c} \sqrt[q]{\left(\frac{\lambda\left(r_E^q(b_i)\right)^\beta}{\left(1-(1-\lambda)r_E^q(b_i)\right)^\beta-(1-\lambda)\left(1-r_E^q(b_i)\right)^\beta} \right)}, \\ \sqrt[q]{\left(\frac{\lambda\left(s_E^q(b_i)\right)^\beta}{\left(1-(1-\lambda)s_E^q(b_i)\right)^\beta-(1-\lambda)\left(1-s_E^q(b_i)\right)^\beta} \right)} \end{array} \right] \end{array} \right\rangle \tag{23}$$

$$\forall i: \left(E_q(b_i)\right)Hmc_\lambda^\beta = \left\langle \begin{array}{c} \left[\begin{array}{c} \sqrt[q]{\left(\frac{\lambda\left(o_E^q(b_i)\right)^\beta}{\left(1-(1-\lambda)o_E^q(b_i)\right)^\beta-(1-\lambda)\left(1-o_E^q(b_i)\right)^\beta} \right)}, \\ \sqrt[q]{\left(\frac{\lambda\left(p_E^q(b_i)\right)^\beta}{\left(1-(1-\lambda)p_E^q(b_i)\right)^\beta-(1-\lambda)\left(1-p_E^q(b_i)\right)^\beta} \right)} \end{array} \right], \\ \left[\begin{array}{c} \sqrt[q]{\left(\frac{\left(1-(1-\lambda)r_E^q(b_i)\right)^\beta-\left(1-r_E^q(b_i)\right)^\beta}{\left(1-(1-\lambda)r_E^q(b_i)\right)^\beta-(1-\lambda)\left(1-r_E^q(b_i)\right)^\beta} \right)}, \\ \sqrt[q]{\left(\frac{\left(1-(1-\lambda)s_E^q(b_i)\right)^\beta-\left(1-s_E^q(b_i)\right)^\beta}{\left(1-(1-\lambda)s_E^q(b_i)\right)^\beta-(1-\lambda)\left(1-s_E^q(b_i)\right)^\beta} \right)} \end{array} \right] \end{array} \right\rangle \tag{24}$$

where $\lambda \in (0, \infty)$ and $\beta > 0$ is considered as a crisp number.

3.4. *IVq-ROF-Hamacher-CIMAS Approach*

CIMAS is proposed by Boskovic et al. (2025) [68] as a novel integrated criteria weighting method that is based on objective evaluation and group decision-making. According to the CIMAS methodology, which is based on expert's judgement, the years of experience related to each expert are acquired as their weight [69–71]. The logic of the CIMAS method is stated as if one expert has more years of experience, his/her criteria evaluation decision is more important than others [72–75]. CIMAS has been applied recently in various fields such as supplier selection [68], financial performance analysis for technology companies [72], sustainable tractor selection in green ports [76], risk prioritization in crowd-shipping from the crowd-shipping provider's perspective [75], website performance analysis in human resource management [73], authentication system selection related to performance appraisal in human resource management [77], and healthcare referral system strategies assessment [69]. In order to prioritize the components related to artificial intelligence (AI)-enabled service quality, IVq-ROF-Hamacher based CIMAS methodology is utilized in this study. As an improved version of the CIMAS approach that includes IVq-ROFS, the method is performed for expert-based criteria prioritizing. IVq-ROFS are preferred for reducing uncertainties related to expert judgements due to presenting as an effective approach to address real-world decision-making problems.

Consider a collection of criteria C_j = {C_1, C_2, …, C_t } with (j = 1, 2, …, t) and a group of decision-makers 〖DM〗_i = { 〖DM〗_1, 〖DM〗_2, …, 〖DM〗_v } with (I = 1, 2, …, v). The application steps related to the IVq-ROF-Hamacher-CIMAS approach are summarized in the following list:

Step 1: The skill related to the each decision-maker is based on the linguistic values (LVs) as shown in Table 1.

Table 1. IVq-ROFNs for calculating the skills related to decision-makers.

Linguistic Terms	IVq-ROFNs
Very good skilled (VGS)	$([0.8, 0.9], [0.1, 0.2])$
Good skilled (GS)	$([0.7, 0.8], [0.2, 0.5])$
Medium skilled (MS)	$([0.5, 0.7], [0.5, 0.7])$
Poor skilled (PS)	$([0.2, 0.5], [0.7, 0.8])$
Very poor skilled (VPS)	$([0.1, 0.2], [0.8, 0.9])$

Source: [74].

Following this, LVs are transformed into the IVq-ROFNs. Finally, the decision-maker matrix related to the skills represented by ($\left(\widetilde{DMM}\right) = \left[\left(\widetilde{DMM_i}\right)\right]_v$) is constructed.

Step 2: To identify the skills related to the decision-makers, the score function matrix represented by $\left(SF = \left[SF\left(\widetilde{DMM_i}\right)\right]_v\right)$ is obtained according to Equation (25).

$$SF\left(\widetilde{DMM_i}\right) = \frac{1}{4}\left[1 + \left(\mu^{Lw}_{\widetilde{DMM_i}}(x)\right)^q - \left(\vartheta^{Lw}_{\widetilde{DMM_i}}(x)\right)^q + 1 + \left(\mu^{Up}_{\widetilde{DMM_i}}(x)\right)^q - \left(\vartheta^{Up}_{\widetilde{DMM_i}}(x)\right)^q\right] \tag{25}$$

where $i = 1, 2, \ldots, v$ and $0 \leq SF\left(\widetilde{DMM_i}\right) \leq 1$.

Step 3: The decision-maker skill weight matrix represented by $(DMSWM = [DMSWM_i]_v)$ is obtained as given below:

$$DMSWM_i = \frac{SF(\widetilde{DMM_i})}{\sum_{i=1}^{v} SF(\widetilde{DMM_i})};\ (i = 1, 2, \ldots, v) \tag{26}$$

Step 4: Each decision-maker (DM_i) assesses each criterion $\left(C_j\right)$ by using LVs given in Table 2. Following this, LVs are transformed into the IVq-ROFNs. After that, criterion assessment matrices $\left(\widetilde{CAM} = \left[\widetilde{CAM_{ij}}\right]_{vt}\right)$ are formed in terms of the judgements provided via decision-makers. Elements related to these matrices are denoted via

$$\widetilde{CAM_{ij}} = \langle \left[\mu^{Lw}_{\widetilde{CAM_{ij}}}(x), \mu^{Up}_{\widetilde{CAM_{ij}}}(x)\right], \left[\vartheta^{Lw}_{\widetilde{CAM_{ij}}}(x), \vartheta^{Up}_{\widetilde{CAM_{ij}}}(x)\right] \rangle \text{with } (i = 1, 2, \ldots, v;\ j = 1, 2, \ldots, t)$$

Table 2. IVq-ROFNs related to the criteria evaluation.

Linguistic Terms	IVq-ROFNs
Exceptionally high (EXH)	$([0.99, 0.99], [0.01, 0.01])$
Extremely high (EH)	$([0.90, 0.90], [0.10, 0.10])$
Very high (VH)	$([0.75, 0.85], [0.05, 0.15])$
High (H)	$([0.60, 0.75], [0.10, 0.20])$
Above average (AA)	$([0.45, 0.60], [0.15, 0.25])$
Average (A)	$([0.50, 0.50], [0.50, 0.50])$
Below average (BA)	$([0.35, 0.45], [0.40, 0.55])$
Low (L)	$([0.25, 0.35], [0.50, 0.60])$
Very low (VL)	$([0.15, 0.20], [0.60, 0.75])$
Extremely low (EL)	$([0.10, 0.10], [0.90, 0.90])$

Source: [71].

Step 5: The weighted criteria assessment matrix $\left(\widetilde{WCAM} = \left[\widetilde{WCAM}_{ij}\right]_{vt}\right)$ is obtained by aggregating the decision-maker matrix $\left(\widetilde{DMM}_i\right)$ and criteria assessment matrix $\left(\widetilde{CAM}_{ij}\right)$ via the IVq-ROF-Hamacher product operation, as given in Equation (27).

$$\widetilde{WCAM}_{ij} = \left\langle \begin{bmatrix} \sqrt[q]{\left(\dfrac{\left(\mu^{Lw}_{\widetilde{DMM}_i}(x)\right)^q\left(\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)\right)^q}{\lambda+(1-\lambda)\left(\left(\mu^{Lw}_{\widetilde{DMM}_i}(x)\right)^q+\left(\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)\right)^q-\left(\mu^{Lw}_{\widetilde{DMM}_i}(x)\right)^q\left(\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)\right)^q\right)}\right)}, \\ \sqrt[q]{\left(\dfrac{\left(\mu^{Up}_{\widetilde{DMM}_i}(x)\right)^q\left(\mu^{Up}_{\widetilde{CAM}_{ij}}(x)\right)^q}{\lambda+(1-\lambda)\left(\left(\mu^{Up}_{\widetilde{DMM}_i}(x)\right)^q+\left(\mu^{Up}_{\widetilde{CAM}_{ij}}(x)\right)^q-\left(\mu^{Up}_{\widetilde{DMM}_i}(x)\right)^q\left(\mu^{Up}_{\widetilde{CAM}_{ij}}(x)\right)^q\right)}\right)} \end{bmatrix}, \begin{bmatrix} \sqrt[q]{\left(\dfrac{\left(\vartheta^{Lw}_{\widetilde{DMM}_i}(x)\right)^q+\left(\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)\right)^q-\left(\vartheta^{Lw}_{\widetilde{DMM}_i}(x)\right)^q\left(\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)\right)^q-(1-\lambda)\left(\vartheta^{Lw}_{\widetilde{DMM}_i}(x)\right)^q\left(\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)\right)^q}{1-(1-\lambda)\left(\vartheta^{Lw}_{\widetilde{DMM}_i}(x)\right)^q\left(\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)\right)^q}\right)}, \\ \sqrt[q]{\left(\dfrac{\left(\vartheta^{Up}_{\widetilde{DMM}_i}(x)\right)^q+\left(\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)\right)^q-\left(\vartheta^{Up}_{\widetilde{DMM}_i}(x)\right)^q\left(\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)\right)^q-(1-\lambda)\left(\vartheta^{Up}_{\widetilde{DMM}_i}(x)\right)^q\left(\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)\right)^q}{1-(1-\lambda)\left(\vartheta^{Up}_{\widetilde{DMM}_i}(x)\right)^q\left(\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)\right)^q}\right)} \end{bmatrix} \right\rangle \tag{27}$$

Step 6: The weighted criteria assessment matrix is transformed into the precise weighted criteria assessment matrix $\left(WCAM = [WCAM_{ij}]_{vt}\right)$ composed of crisp values by applying the score function $\left(SF\left(\widetilde{WCAM}_{ij}\right)\right)$ given as Equation (28).

$$\begin{gathered} SF\left(\widetilde{WCAM}_{ij}\right) = \frac{1}{4}\left[1+\left(\mu^{Lw}_{\widetilde{WCAM}_{ij}}(x)\right)^q-\left(\vartheta^{Lw}_{\widetilde{WCAM}_{ij}}(x)\right)^q+1+\left(\mu^{Up}_{\widetilde{WCAM}_{ij}}(x)\right)^q-\left(\vartheta^{Up}_{\widetilde{WCAM}_{ij}}(x)\right)^q\right]; \\ (i = 1,2,\ldots,v;\ j = 1,2,\ldots,t)\Big|SF\left(\widetilde{WCAM}_{ij}\right) \in [0,1] \end{gathered} \tag{28}$$

where $SF\left(\widetilde{WCAM}_{ij}\right) = WCAM_{ij}$.

Step 7: The normalized criteria assessment matrix $\left(NWCAM = [NWCAM_{ij}]_{vt}\right)$ is obtained via Equation (29).

$$NWCAM_{ij} = \frac{WCAM_{ij}}{\sum_{i=1}^{v} WCAM_{ij}};\ (i = 1,2,\ldots,v;\ j = 1,2,\ldots,t) \tag{29}$$

Step 8: The decision-maker weighted criteria assessment matrix $\left(DMWCAM = [DMWCAM_{ij}]_{vt}\right)$ is formed by utilizing Equation (30), given as follows:

$$DMWCAM_{ij} = NWCAM_{ij}DMSWM_i;\ (i = 1,2,\ldots,v;\ j = 1,2,\ldots,t) \tag{30}$$

Step 9: After acquiring $DMWCAM$, it is necessary to compute the maximum value matrix $\left(DMWCAM^{max} = \left[DMWCAM_j^{max}\right]_t\right)$ and the minimum value matrix $\left(DMWCAM^{min} = \left[DMWCAM_j^{min}\right]_t\right)$ by applying Equations (31) and (32), respectively.

$$DMWCAM_j^{max} = \max_i DMWCAM_{ij};\ (i = 1,2,\ldots,v;\ j = 1,2,\ldots,t) \tag{31}$$

$$DMWCAM_j^{min} = \min_i DMWCAM_{ij};\ (i = 1,2,\ldots,v;\ j = 1,2,\ldots,t) \tag{32}$$

Step 10: The matrix denoting the difference between the maximum and minimum values $\left(DFM = [DFM_j]_t\right)$ is obtained via Equation (33).

$$DFM_j = DMWCAM_j^{max} - DMWCAM_j^{min};(\ j = 1,2,\ldots,t) \tag{33}$$

Step 11: The weight matrix for the criteria $\left(CWM = [CWM_j]_t\right)$ is formed by applying Equation (34).

$$CWM_j = \frac{DFM_j}{\sum_{j=1}^{t} DFM_j};\ (\ j = 1,2,\ldots,t) \tag{34}$$

Step 12: Each decision-maker re-evaluates every criterion as a percentage and the acquired aggregated assessment equals to 100% totally. Then, the second stage in terms of the criteria weighting starts. The second stage weight matrix for the criteria $\left(CWM^* = \left[CWM_j^*\right]_t\right)$ is generated via the mean average. Following that, the reliability index with respect to the criteria (RI) is computed by utilizing Equation (35).

$$RI = \frac{\sum_{j=1}^{t}\left|CWM_j * 100 - CWM_j^*\right|}{100};\ (\ j = 1,2,\ldots,t) \tag{35}$$

If the RI values are lower than 0.1, the results are considered reliable and consistent. Otherwise, the decision-makers need to repeat the criteria weighting process. The methodological framework related to the IVq-ROF-Hamacher-CIMAS method is presented in Figure 1.

3.5. Results and Analysis: A Case Study

A case study was carried out to prioritize the AI-enabled service quality of tourism websites. In order to establish the list of dimensions and their related criteria, decision-makers from academy and industry professionals were contacted and the relevant literature was considered extensively. The complete list of the dimensions and criteria used in the study is given in Table 3 below.

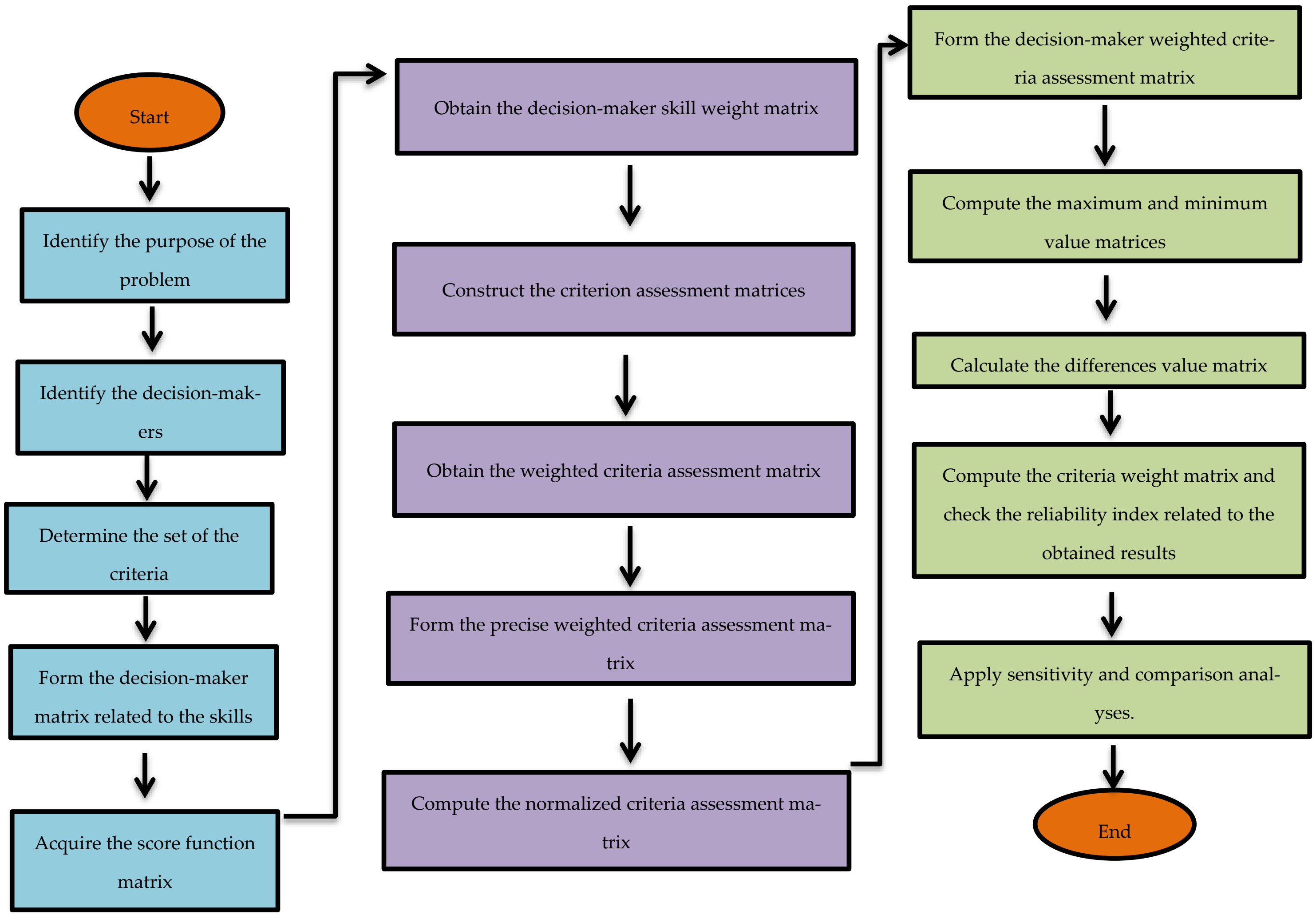

Figure 1. Flowchart showing the steps in the study.

Table 3. Dimensions and related criteria for examining AI-enabled service quality.

Dimension (D)	Criteria (C)	Description	References
D1. Efficiency	C1. Accuracy	AI systems perform correctly at the first attempt	Noor et al. 2022 [30]
	C2. Speed	Tasks are completed in a short time	Huang & Rust 2021 [17]
	C3. Clarity	Interface presents information clearly	Parasuraman et al. 2005 [22]
	C4. Competence	AI sufficiently meets user needs	Mariani et al. 2018 [34]
D2. Security	C5. Risk	No risk in sharing personal data	Belanche et al. 2020 [31]
	C6. Security feeling	Users feel safe sharing sensitive information	Gursoy et al. 2019 [19]
	C7. Protection	Personal data is protected	Beldad et al. 2010 [78]
	C8. Trust	AI will not misuse personal data	Shin 2021 [79]
D3. Availability	C9. Continuity	Systems are always available	Parasuraman et al. 2005 [22]
	C10. Responsiveness load	System is not overloaded	Collier & Bienstock 2006 [80]
	C11. Accessibility	System is reachable anytime	Zeithaml et al. 2002 [21]
D4. Enjoyment	C12. Fun	Using AI is entertaining	Van der Heijden 2004 [81]
	C13. Pleasure	Using AI is enjoyable	Davis 1989 [50]
	C14. Attractiveness	AI use is engaging	Hassenzahl. 2003 [82]
D5. Contact	C15. Access	Human support is reachable	Noor et al. 2022 [30]
	C16. Follow-up	Continuity with human support	Bitner et al. 2000 [83]
	C17. Communication	Live support interaction possible	Gefen & Straub 2004 [63]
	C18. Ease	Getting support is effortless	Parasuraman et al. 1988 [20]
	C19. Information	Contact details are provided	Zeithaml et al. 2002 [21]
D6. Anthropomorphism	C20. Physical similarity	AI has human-like appearance	Epley et al. 2007 [65]
	C21. Personality	AI has a distinct character	Nass & Moon 2000 [60]
	C22. Learning	AI learns about the user over time	Huang & Rust 2021 [17]
	C23. Behavior	AI behaves like a human	Gursoy et al. 2019 [19]
	C24. Personalization	AI provides tailored responses	Tam & Ho 2006 [84]
	C25. Communication style	AI communicates naturally	Luo et al. 2019 [85]

Ten decision-makers were interviewed for evaluating and weighting the dimension based criteria. The decision-makers selected are industry professionals and academicians having the extensive information and experience with respect to AI-enabled service quality.

The main reason for selecting ten decision-makers is that fuzzy multi-criteria decision-making approaches primarily emphasize the quality and expertise of expert judgements rather than large sample sizes. Similar fuzzy MCDM studies in the literature also frequently employ expert panels of comparable size. Therefore, the number of experts used in this study was considered methodologically adequate. In addition, the heterogeneous structure of the expert panel, composed of individuals from different areas of expertise, contributed to a more comprehensive evaluation process and helped reduce the risk of one-dimensional assessments and potential bias.

The decision-makers were selected from different professional backgrounds, including professors, associate professors, lecturers, operational managers, tourism specialists, tourist guides, and hotel general managers. Thus, both academic and practical perspectives were incorporated into the evaluation process. In addition, the CIMAS methodology directly integrates the experience levels of decision-makers into the weighting mechanism, thereby reducing the potential impact of individual bias and increasing the reliability of group evaluations. The reliability index results obtained in the second stage of the analysis also supported the consistency and adequacy of the expert evaluation process.

Detailed information regarding the decision-makers is given in Table 4.

Table 4. Details related to decision-makers.

Decision-Maker	Gender	Profession	Education	Experience (Years)
DM1	Female	Professor	PhD	17
DM2	Male	Lecturer	MSc	12
DM3	Male	Operational Manager	BSc	16
DM4	Male	Tourism Specialist	BSc	6
DM5	Male	Tourist Guide	BSc	12
DM6	Female	Lecturer	MSc	3
DM7	Male	Operational Manager	MSc	14
DM8	Male	Tourism Specialist	BSc	11
DM9	Female	Associate Professor	PhD	11
DM10	Male	Hotel General Manager	MSc	15

In this study five dimensions and a total of twenty five criteria C_j (j = 1, 2, …, 25), and ten decision-makers 〖DM〗_i (r = 1, 2, …, 10) are taken into account. Decision-makers' proficiency levels are determined by taking knowledge levels related to AI-enabled service quality into account. According to the IVq-ROF-Hamacher-CIMAS methodology, decision-makers' skill levels are identified via LVs, as shown in Table 1, and transformed to IVq-ROFNs. The decision-maker matrix related to the skills is then formed and given in Table 5.

Table 5. Decision-makers' skill levels and related SF values.

DMs	Skill Level	IVq-ROFNs	$SF\left(\tilde{DMM}_i\right)$
DM_1	VGS	$[0.8, 0.9], [0.1, 0.2]$	0.8080
DM_2	MS	$[0.5, 0.7], [0.5, 0.7]$	0.5000
DM_3	VGS	$[0.8, 0.9], [0.1, 0.2]$	0.8080
DM_4	PS	$[0.2, 0.5], [0.7, 0.8]$	0.3195
DM_5	MS	$[0.5, 0.7], [0.5, 0.7]$	0.5000
DM_6	VPS	$[0.1, 0.2], [0.8, 0.9]$	0.1920
DM_7	GS	$[0.7, 0.8], [0.2, 0.5]$	0.6805
DM_8	MS	$[0.5, 0.7], [0.5, 0.7]$	0.5000
DM_9	MS	$[0.5, 0.7], [0.5, 0.7]$	0.5000
DM_{10}	VGS	$[0.8, 0.9], [0.1, 0.2]$	0.8080

The score function matrix is obtained via Equation (25) and presented in the last column of the Table 5. Following this, the decision-maker skill weight matrix is acquired by applying Equation (26) and given in Table 6.

Table 6. DM skill weight matrix $(DMSWM = [DMSWM_i]_v)$.

DMs	**DM_1**	**DM_2**	**DM_3**	**DM_4**	**DM_5**
$DMSWM_i$	0.1438	0.0890	0.1438	0.0568	0.0890
DMs	DM_6	DM_7	DM_8	DM_9	DM_{10}
$DMSWM_i$	0.0341	0.1211	0.0890	0.0890	0.1438

After identifying the DM skill weight matrix, each DM assessed each element by utilizing LVs, as given in Table 2. The acquired criteria assessment matrix regarding LVs is presented in Table 7.

Table 7. Criteria assessment matrix with respect to LVs.

DMs	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
DM_1	VH	VH	VH	VH	AA	AA	AA	AA	AA	AA	AA
DM_2	EXH	VH	EXH	EXH	EXH	VH	VH	VH	EXH	EH	EH
DM_3	H	H	VH	VH	VH	VH	VH	VH	EH	VH	EH
DM_4	H	EXH	AA	AA	A	A	A	A	H	H	EXH
DM_5	H	EH	H	AA	EH	EH	VH	EXH	EH	H	VH
DM_6	EXH	AA	H	VH	A	EH	EH	EH	VH	H	VH
DM_7	VH	EH	H	H	A	H	A	VH	H	BA	AA
DM_8	H	H	H	H	EH	EH	EXH	EXH	AA	A	H
DM_9	EXH	EXH	A	EXH	EXH	EXH	EXH	EXH	EH	AA	H
DM_{10}	EXH	EXH	EXH	EH	H	EH	AA	H	EH	EXH	EXH
DMs	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}
DM_1	AA	AA	AA	AA	AA	AA	AA	AA	H	H	H
DM_2	VH	EXH	EXH	EXH	EH	EXH	EXH	EH	VH	VH	VH
DM_3	VH	EXH	EXH	EXH	H	EXH	EXH	EXH	VH	VH	VH
DM_4	EH	EH	EH	A	BA	BA	A	A	BA	BA	BA
DM_5	AA	H	VH	VH	VH	VH	H	H	A	AA	H
DM_6	A	A	A	A	A	AA	A	AA	BA	BA	VH
DM_7	L	L	BA	BA	AA	H	AA	A	A	L	BA
DM_8	AA	BA	A	EXH	EH	EXH	VH	VH	L	VL	EH
DM_9	EL	EL	EL	L	VL	VL	L	VL	EL	EL	A
DM_{10}	A	A	AA	BA	VH	H	AA	EH	A	EH	EXH
DMs	C_{23}	C_{24}	C_{25}								
DM_1	H	H	H								
DM_2	VH	EH	H								
DM_3	VH	VH	VH								
DM_4	BA	BA	BA								
DM_5	A	AA	A								
DM_6	BA	VH	BA								
DM_7	A	H	A								
DM_8	VL	EH	BA								
DM_9	EL	EL	EL								
DM_{10}	VH	EH	EH								

LVs are then transformed into the IVq-ROFNs and resulting criteria assessment matrix composed of IVq-ROFNs is given in Table 8.

Table 8. Criteria assessment matrix in terms of IVq-ROFNs.

	C1				C2				C3			
DMs	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$
DM_1	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15
DM_2	0.99	0.99	0.01	0.01	0.75	0.85	0.05	0.15	0.99	0.99	0.01	0.01
DM_3	0.60	0.75	0.10	0.20	0.60	0.75	0.10	0.20	0.75	0.85	0.05	0.15
DM_4	0.60	0.75	0.10	0.20	0.99	0.99	0.01	0.01	0.45	0.60	0.15	0.25
DM_5	0.60	0.75	0.10	0.20	0.90	0.90	0.10	0.10	0.60	0.75	0.10	0.20
DM_6	0.99	0.99	0.01	0.01	0.45	0.60	0.15	0.25	0.60	0.75	0.10	0.20
DM_7	0.75	0.85	0.05	0.15	0.90	0.90	0.10	0.10	0.60	0.75	0.10	0.20
DM_8	0.60	0.75	0.10	0.20	0.60	0.75	0.10	0.20	0.60	0.75	0.10	0.20
DM_9	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01	0.50	0.50	0.50	0.50
DM_{10}	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01

	C4				C5				C6			
DMs	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$
DM_1	0.75	0.85	0.05	0.15	0.45	0.60	0.15	0.25	0.45	0.60	0.15	0.25
DM_2	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01	0.75	0.85	0.05	0.15
DM_3	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15
DM_4	0.45	0.60	0.15	0.25	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
DM_5	0.45	0.60	0.15	0.25	0.90	0.90	0.10	0.10	0.90	0.90	0.10	0.10
DM_6	0.75	0.85	0.05	0.15	0.50	0.50	0.50	0.50	0.90	0.90	0.10	0.10
DM_7	0.60	0.75	0.10	0.20	0.50	0.50	0.50	0.50	0.60	0.75	0.10	0.20
DM_8	0.60	0.75	0.10	0.20	0.90	0.90	0.10	0.10	0.90	0.90	0.10	0.10
DM_9	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01
DM_{10}	0.90	0.90	0.10	0.10	0.60	0.75	0.10	0.20	0.90	0.90	0.10	0.10

	C7				C8				C9			
DMs	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$
DM_1	0.45	0.60	0.15	0.25	0.45	0.60	0.15	0.25	0.45	0.60	0.15	0.25
DM_2	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15	0.99	0.99	0.01	0.01
DM_3	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15	0.90	0.90	0.10	0.10
DM_4	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.60	0.75	0.10	0.20
DM_5	0.75	0.85	0.05	0.15	0.99	0.99	0.01	0.01	0.90	0.90	0.10	0.10
DM_6	0.90	0.90	0.10	0.10	0.90	0.90	0.10	0.10	0.75	0.85	0.05	0.15
DM_7	0.50	0.50	0.50	0.50	0.75	0.85	0.05	0.15	0.60	0.75	0.10	0.20
DM_8	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01	0.45	0.60	0.15	0.25
DM_9	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01	0.90	0.90	0.10	0.10
DM_{10}	0.45	0.60	0.15	0.25	0.60	0.75	0.10	0.20	0.90	0.90	0.10	0.10

	C10				C11				C12			
DMs	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$
DM_1	0.45	0.60	0.15	0.25	0.45	0.60	0.15	0.25	0.45	0.60	0.15	0.25
DM_2	0.90	0.90	0.10	0.10	0.90	0.90	0.10	0.10	0.75	0.85	0.05	0.15
DM_3	0.75	0.85	0.05	0.15	0.90	0.90	0.10	0.10	0.75	0.85	0.05	0.15
DM_4	0.60	0.75	0.10	0.20	0.99	0.99	0.01	0.01	0.90	0.90	0.10	0.10
DM_5	0.60	0.75	0.10	0.20	0.75	0.85	0.05	0.15	0.45	0.60	0.15	0.25
DM_6	0.60	0.75	0.10	0.20	0.75	0.85	0.05	0.15	0.50	0.50	0.50	0.50
DM_7	0.35	0.45	0.40	0.55	0.45	0.60	0.15	0.25	0.25	0.35	0.50	0.60
DM_8	0.50	0.50	0.50	0.50	0.60	0.75	0.10	0.20	0.45	0.60	0.15	0.25
DM_9	0.45	0.60	0.15	0.25	0.60	0.75	0.10	0.20	0.10	0.10	0.90	0.90
DM_{10}	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01	0.50	0.50	0.50	0.50

Table 8. *Cont.*

	C₁₃				C₁₄				C₁₅			
DMs	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$
DM_1	0.45	0.60	0.15	0.25	0.45	0.60	0.15	0.25	0.45	0.60	0.15	0.25
DM_2	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01
DM_3	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01
DM_4	0.90	0.90	0.10	0.10	0.90	0.90	0.10	0.10	0.50	0.50	0.50	0.50
DM_5	0.60	0.75	0.10	0.20	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15
DM_6	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
DM_7	0.25	0.35	0.50	0.60	0.35	0.45	0.40	0.55	0.35	0.45	0.40	0.55
DM_8	0.45	0.60	0.15	0.25	0.50	0.50	0.50	0.50	0.99	0.99	0.01	0.01
DM_9	0.10	0.10	0.90	0.90	0.10	0.10	0.90	0.90	0.25	0.35	0.50	0.60
DM_{10}	0.50	0.50	0.50	0.50	0.45	0.60	0.15	0.25	0.35	0.45	0.40	0.55

	C₁₆				C₁₇				C₁₈			
DMs	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$
DM_1	0.45	0.60	0.15	0.25	0.45	0.60	0.15	0.25	0.45	0.60	0.15	0.25
DM_2	0.90	0.90	0.10	0.10	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01
DM_3	0.60	0.75	0.10	0.20	0.99	0.99	0.01	0.01	0.99	0.99	0.01	0.01
DM_4	0.35	0.45	0.40	0.55	0.35	0.45	0.40	0.55	0.50	0.50	0.50	0.50
DM_5	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15	0.60	0.75	0.10	0.20
DM_6	0.50	0.50	0.50	0.50	0.45	0.60	0.15	0.25	0.50	0.50	0.50	0.50
DM_7	0.45	0.60	0.15	0.25	0.60	0.75	0.10	0.20	0.45	0.60	0.15	0.25
DM_8	0.90	0.90	0.10	0.10	0.99	0.99	0.01	0.01	0.75	0.85	0.05	0.15
DM_9	0.15	0.20	0.60	0.75	0.15	0.20	0.60	0.75	0.25	0.35	0.50	0.60
DM_{10}	0.75	0.85	0.05	0.15	0.60	0.75	0.10	0.20	0.45	0.60	0.15	0.25

	C₁₉				C₂₀				C₂₁			
DMs	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$
DM_1	0.45	0.60	0.15	0.25	0.60	0.75	0.10	0.20	0.60	0.75	0.10	0.20
DM_2	0.90	0.90	0.10	0.10	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15
DM_3	0.99	0.99	0.01	0.01	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15
DM_4	0.50	0.50	0.50	0.50	0.35	0.45	0.40	0.55	0.35	0.45	0.40	0.55
DM_5	0.60	0.75	0.10	0.20	0.50	0.50	0.50	0.50	0.45	0.60	0.15	0.25
DM_6	0.45	0.60	0.15	0.25	0.35	0.45	0.40	0.55	0.35	0.45	0.40	0.55
DM_7	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.25	0.35	0.50	0.60
DM_8	0.75	0.85	0.05	0.15	0.25	0.35	0.50	0.60	0.15	0.20	0.60	0.75
DM_9	0.15	0.20	0.60	0.75	0.10	0.10	0.90	0.90	0.10	0.10	0.90	0.90
DM_{10}	0.90	0.90	0.10	0.10	0.50	0.50	0.50	0.50	0.90	0.90	0.10	0.10

	C₂₂				C₂₃				C₂₄			
DMs	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\mu^{Up}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Lw}_{\widetilde{CAM}_{ij}}(x)$	$\vartheta^{Up}_{\widetilde{CAM}_{ij}}(x)$
DM_1	0.60	0.75	0.10	0.20	0.60	0.75	0.10	0.20	0.60	0.75	0.10	0.20
DM_2	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15	0.90	0.90	0.10	0.10
DM_3	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15	0.75	0.85	0.05	0.15
DM_4	0.35	0.45	0.40	0.55	0.35	0.45	0.40	0.55	0.35	0.45	0.40	0.55
DM_5	0.60	0.75	0.10	0.20	0.50	0.50	0.50	0.50	0.45	0.60	0.15	0.25
DM_6	0.75	0.85	0.05	0.15	0.35	0.45	0.40	0.55	0.75	0.85	0.05	0.15
DM_7	0.35	0.45	0.40	0.55	0.50	0.50	0.50	0.50	0.60	0.75	0.10	0.20
DM_8	0.90	0.90	0.10	0.10	0.15	0.20	0.60	0.75	0.90	0.90	0.10	0.10
DM_9	0.50	0.50	0.50	0.50	0.10	0.10	0.90	0.90	0.10	0.10	0.90	0.90
DM_{10}	0.99	0.99	0.01	0.01	0.75	0.85	0.05	0.15	0.90	0.90	0.10	0.10

Table 8. *Cont.*

	C25			
DMs	$\mu^{Lw}_{\underset{\sim}{CAM_{ij}}}(x)$	$\mu^{Up}_{\underset{\sim}{CAM_{ij}}}(x)$	$\vartheta^{Lw}_{\underset{\sim}{CAM_{ij}}}(x)$	$\vartheta^{Up}_{\underset{\sim}{CAM_{ij}}}(x)$
DM_1	0.60	0.75	0.10	0.20
DM_2	0.60	0.75	0.10	0.20
DM_3	0.75	0.85	0.05	0.15
DM_4	0.35	0.45	0.40	0.55
DM_5	0.50	0.50	0.50	0.50
DM_6	0.35	0.45	0.40	0.55
DM_7	0.50	0.50	0.50	0.50
DM_8	0.35	0.45	0.40	0.55
DM_9	0.10	0.10	0.90	0.90
DM_{10}	0.90	0.90	0.10	0.10

Then, the weighted criteria assessment matrix is generated according to Equation (27) and the values λ = 1 and q = 3 are considered. The parameter values used in the study were determined based on methodological suitability and consistency considerations reported in the fuzzy MCDM literature. In particular, the q parameter was set as q = 3 in order to provide a broader orthopair fuzzy solution space and to represent expert hesitation more flexibly compared to intuitionistic and Pythagorean fuzzy environments. In addition, λ = 1 was adopted in the Hamacher operator structure because it provides a balanced aggregation process without excessively amplifying optimistic or pessimistic evaluations. These parameter settings were considered appropriate for modelling uncertainty and linguistic ambiguity in expert-based AI-supported service quality evaluation. Following this, the precise weighted criteria assessment matrix is obtained by utilizing the score function, as given in Equation (28) and presented as Table 9.

Table 9. Precise weighted criteria assessment matrix.

DMs	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
DM_1	0.662	0.662	0.662	0.662	0.544	0.544	0.544	0.544	0.544	0.544	0.544
DM_2	0.496	0.448	0.496	0.496	0.496	0.448	0.448	0.448	0.496	0.467	0.467
DM_3	0.600	0.600	0.662	0.662	0.662	0.662	0.662	0.662	0.723	0.662	0.723
DM_4	0.298	0.318	0.290	0.290	0.254	0.254	0.254	0.254	0.298	0.298	0.318
DM_5	0.424	0.467	0.424	0.401	0.467	0.467	0.448	0.496	0.467	0.424	0.448
DM_6	0.191	0.188	0.189	0.190	0.166	0.191	0.191	0.191	0.190	0.189	0.190
DM_7	0.580	0.622	0.537	0.537	0.435	0.537	0.435	0.580	0.537	0.429	0.497
DM_8	0.424	0.424	0.424	0.424	0.467	0.467	0.496	0.496	0.401	0.349	0.424
DM_9	0.496	0.496	0.349	0.496	0.496	0.496	0.496	0.496	0.467	0.401	0.424
DM_{10}	0.798	0.798	0.798	0.723	0.600	0.723	0.544	0.600	0.723	0.798	0.798

Table 9. *Cont.*

DMs	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}
DM_1	0.544	0.544	0.544	0.544	0.544	0.544	0.544	0.544	0.600	0.600	0.600
DM_2	0.448	0.496	0.496	0.496	0.467	0.496	0.496	0.467	0.448	0.448	0.448
DM_3	0.662	0.798	0.798	0.798	0.600	0.798	0.798	0.798	0.662	0.662	0.662
DM_4	0.310	0.310	0.310	0.254	0.258	0.258	0.254	0.254	0.258	0.258	0.258
DM_5	0.401	0.424	0.448	0.448	0.448	0.448	0.424	0.424	0.349	0.401	0.424
DM_6	0.166	0.166	0.166	0.166	0.166	0.188	0.166	0.188	0.170	0.170	0.190
DM_7	0.395	0.395	0.429	0.429	0.497	0.537	0.497	0.435	0.435	0.395	0.429
DM_8	0.401	0.350	0.349	0.496	0.467	0.496	0.448	0.448	0.324	0.267	0.467
DM_9	0.103	0.103	0.103	0.324	0.267	0.267	0.324	0.267	0.103	0.103	0.349
DM_{10}	0.474	0.474	0.544	0.462	0.662	0.600	0.544	0.723	0.474	0.723	0.798

DMs	C_{23}	C_{24}	C_{25}
DM_1	0.600	0.600	0.600
DM_2	0.448	0.467	0.424
DM_3	0.662	0.662	0.662
DM_4	0.258	0.258	0.258
DM_5	0.349	0.401	0.349
DM_6	0.170	0.190	0.170
DM_7	0.435	0.537	0.435
DM_8	0.267	0.467	0.350
DM_9	0.103	0.103	0.103
DM_{10}	0.662	0.723	0.723

With respect to the normalization process according to Equation (29), the normalized criteria assessment matrix is generated and given in Table 10.

Table 10. Normalized criteria assessment matrix.

DMs	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
DM_1	0.133	0.131	0.137	0.135	0.118	0.113	0.120	0.114	0.112	0.119	0.112
DM_2	0.099	0.089	0.102	0.101	0.108	0.093	0.099	0.093	0.102	0.102	0.096
DM_3	0.120	0.119	0.137	0.135	0.144	0.138	0.146	0.138	0.149	0.145	0.149
DM_4	0.060	0.063	0.060	0.059	0.055	0.053	0.056	0.053	0.061	0.065	0.065
DM_5	0.085	0.093	0.087	0.082	0.101	0.097	0.099	0.104	0.096	0.092	0.092
DM_6	0.038	0.037	0.039	0.039	0.036	0.039	0.042	0.040	0.039	0.041	0.039
DM_7	0.116	0.123	0.111	0.109	0.094	0.112	0.096	0.121	0.110	0.094	0.102
DM_8	0.085	0.084	0.087	0.086	0.101	0.097	0.109	0.104	0.082	0.076	0.087
DM_9	0.099	0.098	0.072	0.101	0.108	0.103	0.109	0.104	0.096	0.087	0.087
DM_{10}	0.160	0.158	0.165	0.148	0.130	0.150	0.120	0.125	0.149	0.174	0.165

Table 10. *Cont.*

DMs	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}
DM_1	0.139	0.133	0.129	0.123	0.124	0.117	0.120	0.119	0.156	0.148	0.129
DM_2	0.114	0.122	0.118	0.112	0.106	0.107	0.110	0.102	0.117	0.111	0.096
DM_3	0.169	0.196	0.190	0.180	0.136	0.172	0.177	0.175	0.173	0.164	0.143
DM_4	0.079	0.076	0.074	0.057	0.058	0.055	0.056	0.055	0.067	0.064	0.055
DM_5	0.102	0.104	0.106	0.101	0.102	0.096	0.094	0.093	0.091	0.099	0.091
DM_6	0.042	0.040	0.039	0.037	0.037	0.040	0.036	0.041	0.044	0.042	0.041
DM_7	0.101	0.097	0.102	0.097	0.113	0.115	0.110	0.095	0.113	0.098	0.092
DM_8	0.102	0.086	0.083	0.112	0.106	0.107	0.099	0.098	0.084	0.066	0.101
DM_9	0.026	0.025	0.024	0.073	0.061	0.057	0.072	0.058	0.027	0.025	0.075
DM_{10}	0.121	0.116	0.129	0.104	0.151	0.129	0.120	0.158	0.123	0.179	0.172

DMs	C_{23}	C_{24}	C_{25}
DM_1	0.151	0.135	0.147
DM_2	0.113	0.106	0.104
DM_3	0.167	0.150	0.162
DM_4	0.065	0.058	0.063
DM_5	0.088	0.090	0.085
DM_6	0.043	0.043	0.041
DM_7	0.109	0.121	0.106
DM_8	0.067	0.106	0.085
DM_9	0.026	0.023	0.025
DM_{10}	0.167	0.163	0.177

Then, the DM-weighted criteria assessment matrix is generated by applying Equation (30). The results are shown in Table 11.

Table 11. DM-weighted criteria assessment matrix.

DMs	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
DM_1	0.0191	0.0189	0.0197	0.0195	0.0170	0.0163	0.0173	0.0164	0.0161	0.0171	0.0161
DM_2	0.0088	0.0079	0.0091	0.0090	0.0096	0.0083	0.0088	0.0083	0.0091	0.0091	0.0086
DM_3	0.0173	0.0171	0.0197	0.0195	0.0207	0.0198	0.0210	0.0199	0.0214	0.0208	0.0215
DM_4	0.0034	0.0036	0.0034	0.0033	0.0031	0.0030	0.0032	0.0030	0.0035	0.0037	0.0037
DM_5	0.0075	0.0082	0.0078	0.0073	0.0090	0.0086	0.0088	0.0092	0.0085	0.0082	0.0082
DM_6	0.0013	0.0012	0.0013	0.0013	0.0012	0.0013	0.0014	0.0013	0.0013	0.0014	0.0013
DM_7	0.0141	0.0149	0.0134	0.0133	0.0114	0.0135	0.0116	0.0147	0.0134	0.0114	0.0124
DM_8	0.0075	0.0075	0.0078	0.0077	0.0090	0.0086	0.0097	0.0092	0.0073	0.0068	0.0078
DM_9	0.0088	0.0087	0.0064	0.0090	0.0096	0.0092	0.0097	0.0092	0.0085	0.0078	0.0078
DM_{10}	0.0231	0.0228	0.0237	0.0213	0.0188	0.0217	0.0173	0.0180	0.0214	0.0251	0.0237

Table 11. *Cont.*

DMs	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}
DM_1	0.0200	0.0192	0.0186	0.0177	0.0178	0.0168	0.0173	0.0171	0.0225	0.0214	0.0186
DM_2	0.0102	0.0108	0.0105	0.0099	0.0095	0.0095	0.0098	0.0091	0.0104	0.0099	0.0086
DM_3	0.0244	0.0282	0.0274	0.0259	0.0197	0.0247	0.0255	0.0252	0.0249	0.0236	0.0205
DM_4	0.0045	0.0043	0.0042	0.0032	0.0033	0.0031	0.0032	0.0031	0.0038	0.0036	0.0031
DM_5	0.0091	0.0092	0.0095	0.0090	0.0091	0.0086	0.0083	0.0083	0.0081	0.0088	0.0081
DM_6	0.0014	0.0013	0.0013	0.0012	0.0012	0.0013	0.0012	0.0014	0.0015	0.0014	0.0014
DM_7	0.0122	0.0117	0.0124	0.0117	0.0137	0.0140	0.0134	0.0115	0.0137	0.0118	0.0112
DM_8	0.0091	0.0076	0.0074	0.0099	0.0095	0.0095	0.0088	0.0087	0.0075	0.0059	0.0089
DM_9	0.0023	0.0022	0.0022	0.0065	0.0054	0.0051	0.0064	0.0052	0.0024	0.0022	0.0067
DM_{10}	0.0174	0.0167	0.0186	0.0150	0.0217	0.0186	0.0173	0.0228	0.0178	0.0258	0.0248
DMs	C_{23}	C_{24}	C_{25}								
DM_1	0.0218	0.0195	0.0211								
DM_2	0.0100	0.0094	0.0092								
DM_3	0.0240	0.0216	0.0233								
DM_4	0.0037	0.0033	0.0036								
DM_5	0.0078	0.0080	0.0076								
DM_6	0.0014	0.0014	0.0014								
DM_7	0.0133	0.0147	0.0129								
DM_8	0.0060	0.0094	0.0076								
DM_9	0.0023	0.0020	0.0022								
DM_{10}	0.0240	0.0235	0.0255								

The maximum, minimum and difference matrices are calculated by utilizing Equations (31)–(33), respectively, and given in Table 12.

Table 12. The maximum, minimum and difference matrices.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
$DMWCAM_j^{max}$	0.0231	0.0228	0.0237	0.0213	0.0207	0.0217	0.0210	0.0199	0.0214	0.0251	0.0237
$DMWCAM_j^{min}$	0.0013	0.0012	0.0013	0.0013	0.0012	0.0013	0.0014	0.0013	0.0013	0.0014	0.0013
DFM_j	0.0217	0.0215	0.0224	0.0199	0.0195	0.0203	0.0196	0.0186	0.0201	0.0237	0.0224
	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}
$DMWCAM_j^{max}$	0.0244	0.0282	0.0274	0.0259	0.0217	0.0247	0.0255	0.0252	0.0249	0.0258	0.0248
$DMWCAM_j^{min}$	0.0014	0.0013	0.0013	0.0012	0.0012	0.0013	0.0012	0.0014	0.0015	0.0014	0.0014
DFM_j	0.0229	0.0268	0.0260	0.0247	0.0204	0.0233	0.0242	0.0238	0.0233	0.0243	0.0234
	C_{23}	C_{24}	C_{25}								
$DMWCAM_j^{max}$	0.0240	0.0235	0.0255								
$DMWCAM_j^{min}$	0.0014	0.0014	0.0014								
DFM_j	0.0226	0.0221	0.0240								

Then, the criteria weight matrix is acquired by applying Equation (34) and the results presented in Table 12.

According to Table 13, while Pleasure (C_13) was found to be the most important of the criteria, having a value of 0.04776; Security (C_8) was revealed as the least essential, as indicated by the value of 0.03308.

Table 13. The weight matrix for criteria.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
CWM_j	0.03871	0.03834	0.03983	0.03548	0.03470	0.03616	0.03491	0.03308	0.03574	0.04219	0.03981
Rank	17	18	14	22	24	20	23	25	21	8	15
Criteria	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}
CWM_j	0.04079	0.04776	0.04631	0.04390	0.03638	0.04158	0.04315	0.04234	0.04156	0.04331	0.04160
Rank	12	1	2	3	19	10	5	7	11	4	9
Criteria	C_{23}	C_{24}	C_{25}								
CWM_j	0.04018	0.03928	0.04280								
Rank	13	16	6								

As the second stage related to the criteria weighting process, each DM was re-examined for each criterion as a percentage. Then, the calculations with respect to the RI were made via Equation (35). The obtained RI value (0.061), which remains below the threshold of 0.1, showed that the results are considered as reliable and consistent.

3.6. Sensitivity Analysis

In this study, a sensitivity analysis was executed in two stages for testing the validity and reliability of the IVq-ROF-Hamacher-CIMAS approach. In the first part, the impact of parameter λ related to the criteria ranking performance was assessed. The impact of parameter q for the criteria ranking performance was examined in the second part. In the third part, the impacts of assigning different weights to DMs on the criteria ranking performance were evaluated.

3.6.1. Variation Related to the Parameter λ

Sensitivity analysis related to the proposed model was performed in the initial stage using 39 different scenarios, in which the parameter λ was varied between 0 and 4. According to the first scenario ($S0$), the value of the parameter $\lambda = 1$ was considered. The results for the first stage in terms of the sensitivity analysis are shown in Figure 2.

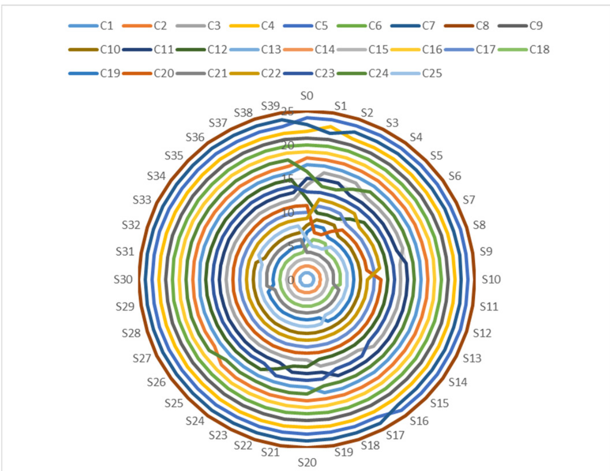

Figure 2. Ranking changes related to the criteria according to the variation in terms of parameter λ.

As seen from Figure 2, minor changes are observed in the ranking of criteria across the 39 scenarios formed towards the variation in parameter λ. The same ranking results were obtained for two of the scenarios and the average Spearman rank correlation coefficient (SRCC) value among the results of all the scenarios was obtained as 99.14%. SRCC moves in the interval of [0.98, 1.00], indicating a high correlation between the ranking results of the proposed IVq-ROF-Hamacher-CIMAS approach and the ranking results of the different scenarios. While C13 remained the best criterion for all scenarios, C14 and C15 were acquired as the second- and third-best criteria, respectively. On the other hand, C8 was obtained as the last criterion for all the created scenarios. These findings show that the proposed model is stable and less sensitive towards the variation in parameter λ.

3.6.2. Variation Related to the Parameter q

For the second stage, the sensitivity analysis variation related to parameter q was examined under a total of 78 different scenarios. The first 39 scenarios were developed for parameter $q = 4$, and λ was varied between 0 and 4. The following 39 scenarios were constructed for $q = 5$, and λ was changed between 0 and 4. The results related to the second stage in terms of the sensitivity analysis are presented in Figures 3 and 4.

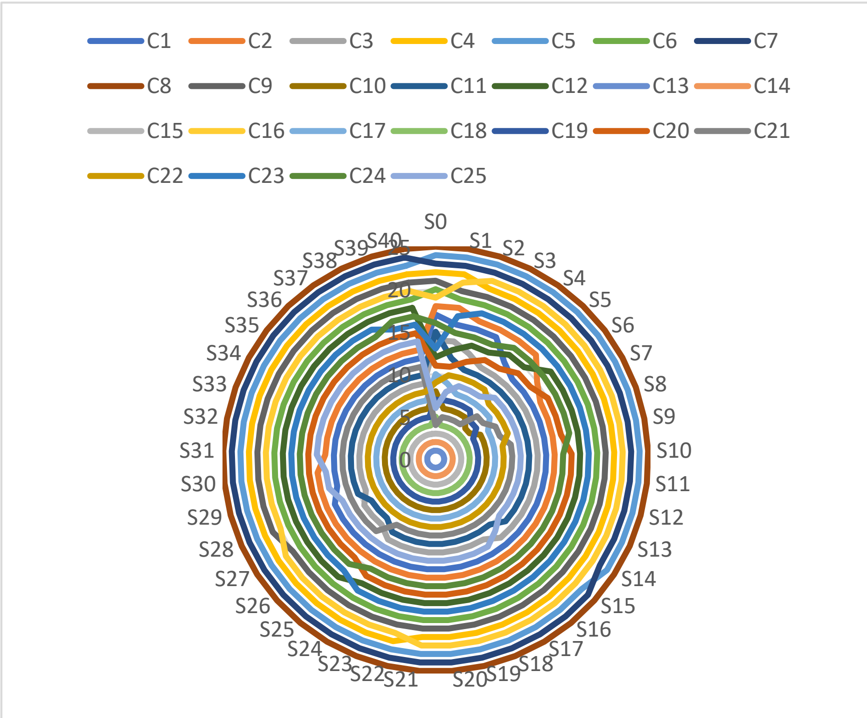

Figure 3. Ranking changes related to the criteria for the case of $q = 4$.

According to the Figures 3 and 4, minor changes are observed in the ranking of criteria across the first and second 39 scenarios that were created for parameter $q = 4$ and $q = 5$. While the average SRCC value among the results for the first 39 scenarios was 91.26%, it was 86.04% for the second 39 scenarios. SRCC moves in the interval [0.85, 0.98], denoting a high correlation between the ranking results of the proposed approach and the ranking results of the various scenarios. C13 and C14 remained as the best and second-best criteria for all scenarios, respectively. On the other hand, C8 was revealed as the last criterion for all of the scenarios. These findings indicate that the proposed approach is stable and less sensitive towards the variation in terms of parameter q.

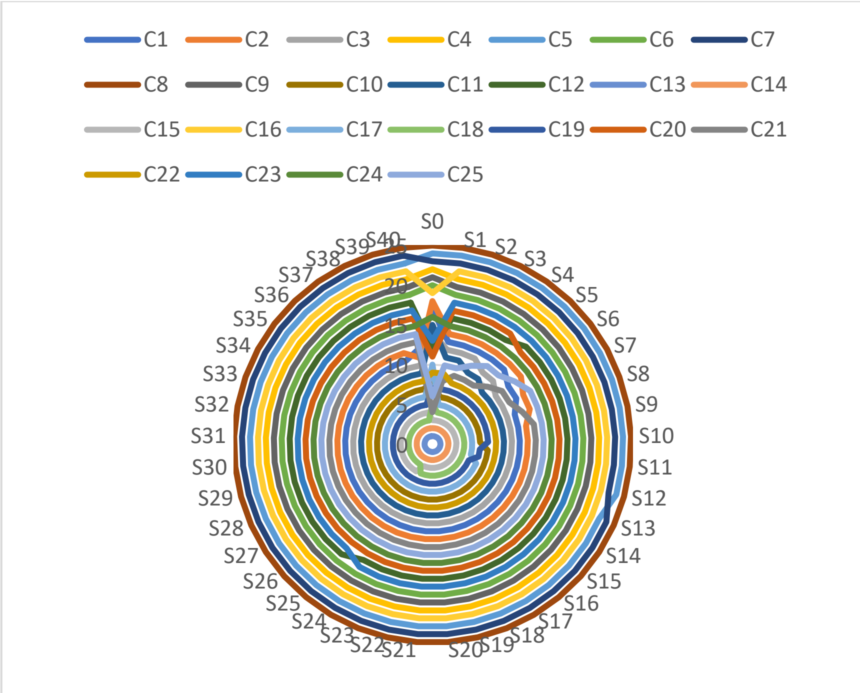

Figure 4. Ranking changes related to the criteria for the case of $q = 5$.

3.6.3. Examining the Impacts of Assigning Various Weights to DMs

According to the third stage of the sensitivity analysis, a total of 710 scenarios were created by assigning different weights to DMs related to the their experience levels. The results of the third stage in terms of sensitivity analysis are depicted in Figure 5.

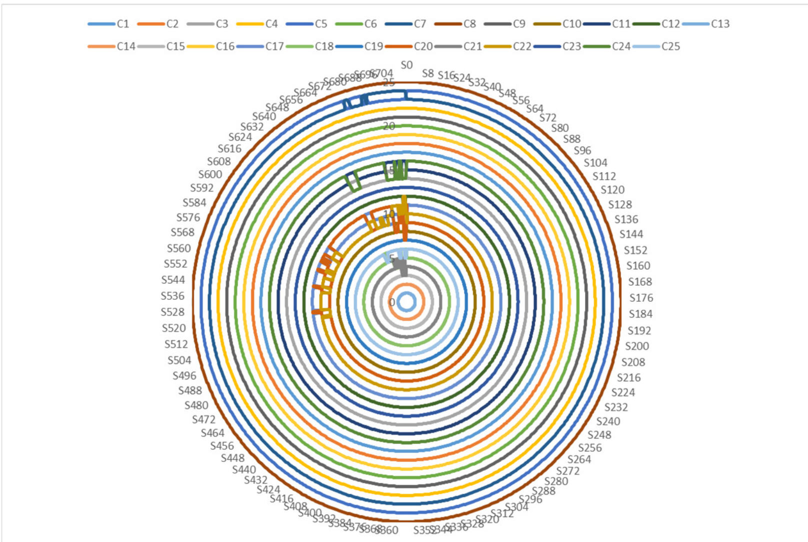

Figure 5. Ranking changes related to the criteria by assigning different weights to DMs.

As can be seen in Figure 5, slight variations are found in the ranking of criteria in the scenarios towards to the assigning various weights to DMs. The same ranking results were obtained for 84 scenarios, and the average SRCC value among the results for all the scenarios was found to be 99.78%. While C13 and C14 were obtained as the first and second-best criteria for all scenarios, respectively, C15 was determined to be the third-best criterion for 702 scenarios (98.87%). On the other hand, C8 was found to be the last criterion for all the scenarios. The ranking results concerning the IVq-ROF-Hamacher-CIMAS approach and the 710 scenarios generated were examined via SRCC. All correlation coefficients are greater than 0.98, showing a high correlation between the ranking results of the proposed model and the ranking results of the various scenarios. The results obtained from the SRCC show that assigning various weights to DMs does not significantly affect the final ranking of the proposed IVq-ROF-Hamacher-CIMAS approach. In general, the proposed model is considered stable, valid, robust and less sensitive towards assigning different weights to DMs.

3.6.4. Comparison Analysis

To examine the reliability related to the ranking result obtained from the proposed IVq-ROF-Hamacher-CIMAS approach, a comparison analysis was made with other MCDM methods, namely IVq-ROF-SWARA and IVq-ROF-AHP, in terms of the SRCC values, and shown in Table 14. In addition, the ranking results with respect to the comparison analysis are denoted in Figure 6.

Table 14. Results related to the comparison analysis.

Criteria	IVq-ROF-CIMAS	IVq-ROF-SWARA	IVq-ROF-AHP
C1	17	17	17
C2	18	19	18
C3	14	12	12
C4	22	21	22
C5	24	23	24
C6	20	22	21
C7	23	24	23
C8	25	25	25
C9	21	20	20
C10	8	9	9
C11	15	16	16
C12	12	10	10
C13	1	2	1
C14	2	1	2
C15	3	4	3
C16	19	18	19
C17	10	13	11
C18	5	3	4
C19	7	7	8
C20	11	11	13
C21	4	5	5
C22	9	6	6
C23	13	14	14
C24	16	15	15
C25	6	8	7
		SRCC = 0.98	**SRCC = 0.987**

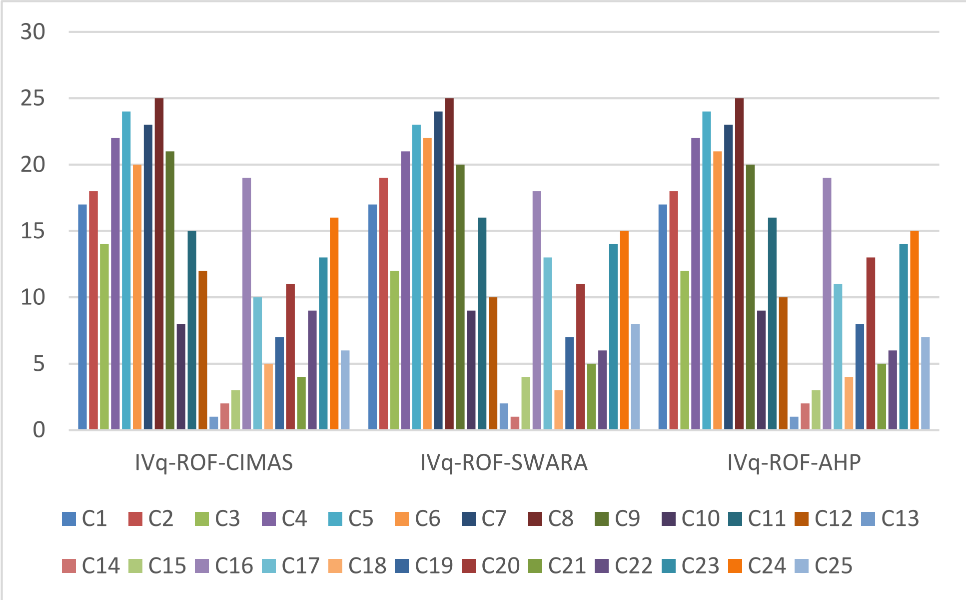

Figure 6. Ranking of criteria according to various MCDM methods.

When examining the results related to the comparison analysis, Figure 3 shows that there were minor changes concerning the ranking of the criteria. According to the acquired values given in Table 14, the average SRCC value of the IVq-ROF-Hamacher-CIMAS approach with other MCDM methods is found as 0.983. In terms of the SRCC values, a statistically significant (at 1% level) and high correlation was found between the IVq-ROF-Hamacher-CIMAS approach and other MCDM methods. The proposed IVq-ROF-Hamacher-CIMAS approach presents consistent and reliable results when compared with other MCDM methods.

In addition to the comparison analysis, other fuzzy set extensions (such as T-Spherical and Fermatean) that use the Hamacher aggregation operator were applied. The ranking results are presented in Figure 7.

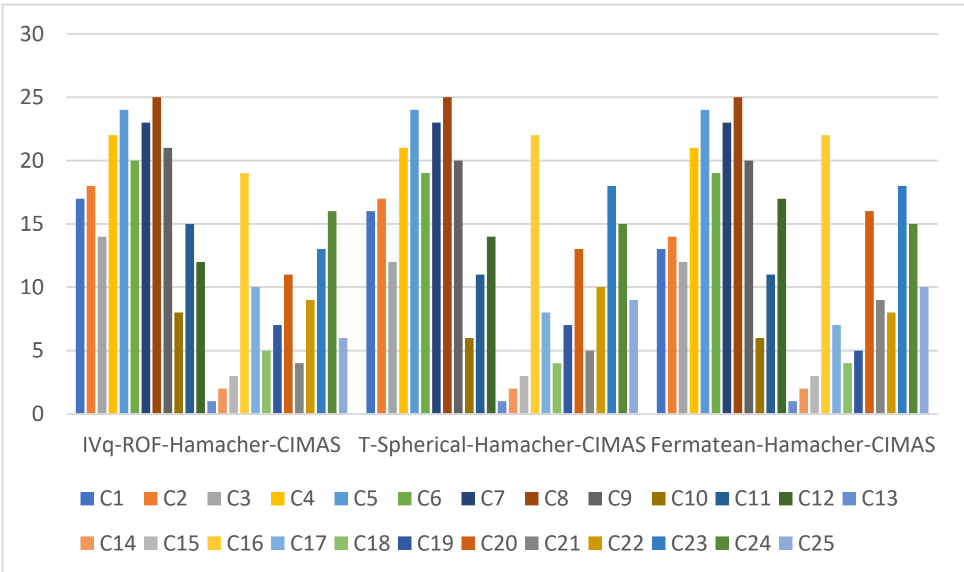

Figure 7. Ranking of criteria according to different fuzzy set extensions that use the Hamacher aggregation operator.

According to Figure 7, there are minor changes seen in terms of the ranking of the criteria. While C13 was found to be the best criterion, C14 and C15 were ranked as the second- and third-best criteria, respectively. On the other hand, C8 was revealed as the last criterion. The average SRCC value of the IVq-ROF-Hamacher-CIMAS approach with other fuzzy set extensions using Hamacher aggregation operator-based CIMAS method was found as 0.944. The proposed IVq-ROF-Hamacher-CIMAS approach shows reliable results when compared with other fuzzy set extensions using the Hamacher aggregation operator-based CIMAS method.

Finally a comparison analysis was executed with other aggregation operators (such as Dombi–Bonferroni, Aczel–Alsina and Hamy mean) in terms of IVq-ROF sets-based CIMAS. The ranking results are given in Figure 8.

There are minor changes in terms of the ranking of the criteria when the results given in Figure 8 are considered. While C13 was found to be the best criterion, C8 was the last. The average SRCC value of the IVq-ROF-Hamacher-CIMAS approach with other aggregation operators was found to be 0.919. The proposed IVq-ROF-Hamacher-CIMAS approach shows valid, consistent and reliable results when compared with other aggregation operators in terms of the IVq-ROF sets-based CIMAS method.

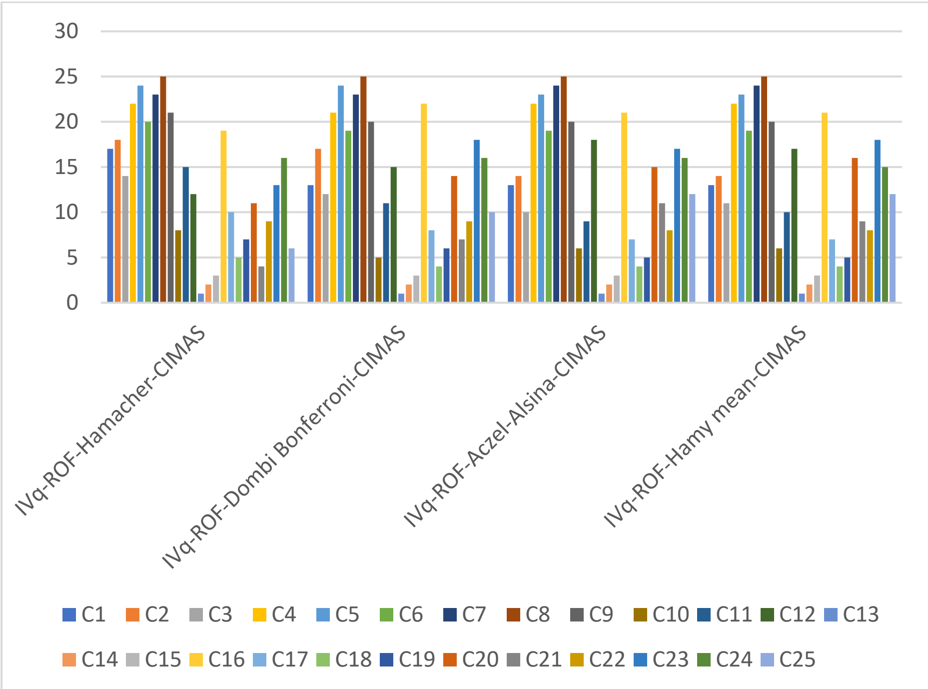

Figure 8. Ranking of criteria according to various aggregation operators.

4. Discussion

This study presents an integrated methodological framework capable of simultaneously modelling uncertainty, decision-maker hesitations and interactions between criteria—aspects that have been addressed only to a limited extent in the literature—with a view to evaluating the quality of AI-supported e-tourism services. In this context, the proposed interval-valued q-rung orthopair fuzzy Hamacher-CIMAS approach, distinguishing itself from classical multi-criteria decision-making methods, directly integrates the linguistic uncertainties and interval-based judgements inherent in expert evaluations into the analytical process. The q-rung orthogonal fuzzy structure represents decision-makers' uncertainties in a more flexible and realistic manner by handling membership and anti-membership degrees across a broad solution space, whilst Hamacher operators enable the parametric and consistent integration of interactions between criteria. Furthermore, the CIMAS method's incorporation of the decision-maker's experience into the weighting process offers a unique contribution that enhances the reliability of evaluations in group decision-making problems. This integrated approach not only produces more discriminatory results in the determination of criterion weights, but also enables a more realistic modelling of decision-making problems under uncertainty. In this respect, the study makes a highly generalizable and methodologically innovative contribution to both the literature on AI-supported service quality and to fuzzy multi-criteria decision-making methods.

The findings reveal that service quality is shaped not only by technical performance but also by experiential and interactive elements. In particular, the fact that the 'pleasure' (C13) criterion carries the highest weight indicates that hedonic value plays a central role in the perception of service quality. This finding is consistent with studies showing that user behaviour in hedonic information systems is shaped by experience and perceived pleasure [78]. Similarly, it has been shown that the intention to use technology is not solely benefit-based but is also related to intrinsic motivation and pleasure [50]. This effect appears to be more pronounced in experience-oriented sectors such as tourism. From a theoretical perspective, these findings suggest that AI-supported service quality should be evaluated not only through operational and functional performance but also through experiential and interaction-oriented dimensions. In particular, the prominence of enjoyment, communication, and anthropomorphism criteria indicates that users perceive AI-supported tourism services as socio-technical systems involving emotional and social interaction processes. In this respect, the study contributes to the AISAQUAL literature by supporting a more multidimensional understanding of AI-supported service quality under conditions of uncertainty.

The fact that criteria relating to efficiency remain at a moderate level indicates that these factors are now perceived by users as the expected standard. Classical models of electronic service quality define efficiency as a fundamental service component [22]. However, recent studies have shown that artificial intelligence systems derive their competitive advantage not only from operational efficiency but also from cognitive and emotional contributions [17]. In this context, the findings suggest that differentiation in AI-supported services is achieved through experiential elements.

In terms of the security dimension, the fact that the 'trust' (C8) criterion has the lowest weighting indicates that this dimension is regarded as a 'threshold condition'. It is known that users make decisions in digital environments based on a balance of benefits and risks [54]. Furthermore, it is stated that whilst trust is a critical element in online environments, it often functions as an invisible prerequisite [80]. Consequently, security emerges not so much as a determinant of service quality but rather as a fundamental requirement.

In terms of accessibility and performance continuity, the fact that the system's capacity to respond under high load takes centre stage highlights the importance of dynamic performance in digital service quality. It has been clearly demonstrated in the literature that service quality is related not only to access but also to process performance and system reliability [79].

The fact that access to human support and the ease of support rank highly in the communication dimension indicates that artificial intelligence systems should be evaluated as hybrid service systems rather than fully automated structures. It is emphasized that human interaction is a critical complement in technology-supported services [83].

In terms of anthropomorphism, the prominence of criteria such as personality, communication style and learning capacity indicates that users perceive artificial intelligence as a social actor. This finding is consistent with studies showing that individuals respond

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to technology as if it were a social entity [66]. However, the fact that physical similarity remains of lower importance suggests that the behavioural and communicative dimensions of anthropomorphism are more critical than the visual ones [65]. Recent studies also demonstrate that AI-supported interactions enhance the user experience by increasing the perception of the AI as a social entity [86].

Overall, the results indicate that the quality of AI-supported e-tourism services has evolved from technological performance towards experiential value. This transformation can be attributed to both changes in user expectations and the advanced interaction and personalization capabilities offered by AI technologies [17,19]. At the same time, the findings also suggest several critical implications regarding the future development of AI-supported tourism services. The relatively lower importance assigned to purely functional and security-related criteria may indicate that users increasingly perceive these dimensions as basic expectations rather than sources of competitive differentiation. However, this situation may also create potential risks for service providers, since excessive emphasis on experiential and anthropomorphic features could overshadow issues related to transparency, privacy, and ethical AI use. In this respect, the results highlight the necessity in maintaining a balance between emotional interaction, technological efficiency, and responsible AI practices in the design of AI-supported tourism services.

5. Conclusions and Implications

Consequently, this study not only reveals the multidimensional structure of AI-supported service quality but also clearly demonstrates the methodological superiority of the IVq-ROF-Hamacher-CIMAS approach used in analysing this structure. In particular, the joint consideration of uncertainty, decision-maker hesitations and interactions between criteria has ensured the attainment of more realistic and discriminatory results compared to classical methods. In this respect, the study makes a significant contribution to both the literature on AI-supported service quality and fuzzy multi-criteria decision-making methods. It is recommended that future studies test this method in different contexts and compare it with alternative fuzzy models.

The proposed IVq-ROF-Hamacher-CIMAS approach provides important practical implications for digital tourism platforms and AI-supported service systems. In particular, it contributes to a more analytical and systematic identification of which service quality dimensions should be prioritized by businesses using online travel platforms, smart reservation systems, virtual assistants, chatbot applications, and personalized recommendation systems. The findings indicate that dimensions such as efficiency, security, availability/accessibility, communication and interaction quality, user experience and hedonic elements (enjoyment), as well as anthropomorphic characteristics, play a decisive role in shaping user perceptions within AI-supported e-tourism services.

Accordingly, tourism businesses may allocate their resources more strategically in order to enhance user satisfaction, digital service performance, and customer loyalty. In particular, increasing investments in security and data privacy is critically important for strengthening user trust. Similarly, the development of AI-based systems that provide accessibility and rapid service delivery may improve user platform experiences and support service continuity. In terms of communication and interaction quality, the development of chatbots and virtual assistant systems with more advanced natural language processing capabilities may contribute to making the user experience more personalized and human-like.

Furthermore, the prominence of anthropomorphic features and hedonic experience elements demonstrates that digital tourism platforms are evolving beyond purely functional service structures into experience-oriented interaction environments. This highlights the importance of design strategies capable of increasing users' emotional attachment from the perspective of platform managers. In addition, the proposed approach may serve as an effective decision-support tool in service design, digital transformation strategies, AI-based customer experience management, and service quality optimization processes by enabling decision-makers to conduct more consistent and reliable evaluations under uncertainty.

Finally, the proposed methodological framework is not limited solely to the e-tourism sector; it may also be applied to e-commerce, digital banking, healthcare services, smart customer service systems, and other AI-supported digital service sectors. In this respect, the study presents an evaluation model that is expandable both theoretically and practically and adaptable to different multi-criteria decision-making problems.

There are some limitations related to the study. The first limitation is related to the set of criteria. The criteria set is derived from the literature review and expert judgements and it can be expanded in terms of different application areas. Secondly, this study is based on the case of Türkiye and includes evaluations obtained from academics and industry experts operating in the Turkish tourism sector. Therefore, the findings may reflect country-specific and cultural characteristics, which may limit the international generalizability of the results. Future studies may enhance external validity by employing multinational expert panels and conducting cross-country comparative analyses. Third, the study is limited by the number of decision-makers (DMs) included in the evaluation process. Although the selected experts have relevant academic and sectoral experience, a larger and more diverse DM panel could improve the statistical robustness, reliability, and generalizability of the weighting results. In addition, the practical applicability of the proposed framework may be further enhanced by integrating actual user feedback, behavioural data, and customer experience evaluations obtained from users of AI-supported e-tourism services. Future studies may also benefit from including decision-makers from different disciplinary, institutional, and cultural backgrounds in order to reduce potential bias and strengthen external validity. Future studies may also focus on developing user-friendly decision support tools and software-based applications to improve the practical applicability, computational efficiency, and scalability of the proposed framework. In addition, future studies may employ longitudinal data and dynamic updating approaches to capture temporal changes in AI-supported e-tourism service quality perceptions.

In future studies, the proposed model's applicability may be increased by its application in various fields and by including additional dimension-based criteria. Further, a detailed comparison with other aggregation techniques (Dom-bi-Bonferroni [87], Aczel-Alsina [88], Frank [89], Hamy mean [90], etc.) via different fuzzy set extensions (Spherical [91], Fermatean [92], Fractal [93], Circular Intuitionistic [94], Gaussian Intuitionistic [95], etc.) will present better decisions in uncertain, imprecise and complex environments.

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References

1. Wallenius, J.; Dyer, J.S.; Fishburn, P.C.; Steuer, R.E.; Zionts, S.; Deb, K. Multiple criteria decision making, multiattribute utility theory: Recent accomplishments and what lies ahead. *Manag. Sci.* **2008**, *54*, 1336–1349. [CrossRef]
2. Keeney, R.L.; Raiffa, H. *Decisions with Multiple Objectives: Preferences and Value Trade-Offs*; Cambridge University Press: Cambridge, UK, 1993; ISBN 0-521-43883-7.
3. Belton, V.; Stewart, T.J. *Multiple Criteria Decision Analysis: An Integrated Approach*; Springer: New York, NY, USA, 2002. [CrossRef]

4. Greco, S.; Ehrgott, M.; Figueira, J.R. *Multiple Criteria Decision Analysis*, 2nd ed.; International Series in Operations Research and Management Science: New York, NY, USA, 2016. [CrossRef]
5. Ishizaka, A.; Nemery, P. *Multi-Criteria Decision Analysis: Methods and Software*; John Wiley & Sons: Hoboken, NJ, USA, 2013; ISBN 978-1-119-97407-9. Available online: https://download.e-bookshelf.de/download/0003/8460/95/L-G-0003846095-0002367570.pdf (accessed on 15 February 2026).
6. Kahraman, C.; Onar, S.C.; Oztaysi, B. Fuzzy multicriteria decision-making: A literature review. *Int. J. Comput. Intell. Syst.* **2015**, *8*, 637–666. [CrossRef]
7. Zadeh, L.A. Fuzzy sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]
8. Cinelli, M.; Kadziński, M.; Gonzalez, M.; Słowiński, R. How to support the application of multiple criteria decision analysis? Let us start with a comprehensive taxonomy. *Omega* **2020**, *96*, 102261. [CrossRef] [PubMed]
9. Durbach, I.N.; Stewart, T.J. Modeling uncertainty in multi-criteria decision analysis. *Eur. J. Oper. Res.* **2012**, *223*, 1–14. [CrossRef]
10. Mardani, A.; Jusoh, A.; Nor, K.M.; Khalifah, Z.; Zakwan, N.; Valipour, A. Multiple criteria decision-making techniques and their applications—A review. *Econ. Res. Ekon. Istraživanja* **2015**, *28*, 516–571. [CrossRef]
11. Tussyadiah, I. A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism. *Ann. Tour. Res.* **2020**, *81*, 102883. [CrossRef]
12. Buhalis, D.; Law, R. Progress in information technology and tourism management: 20 years on and 10 years after the Internet. *Tour. Manag.* **2008**, *29*, 609–623. [CrossRef]
13. Ivanov, S.; Webster, C. Economic fundamentals of robotics in tourism. *Ann. Tour. Res.* **2019**, *75*, 292–302. [CrossRef]
14. Dwivedi, Y.K.; Kshetri, N.; Hughes, L.; Slade, E.L.; Jeyaraj, A.; Kar, A.K.; Baabdullah, A.M.; Koohang, A.; Raghavan, V.; Ahuja, M.; et al. So what if ChatGPT wrote it? Multidisciplinary perspectives on generative AI. *Int. J. Inf. Manag.* **2023**, *71*, 102642. [CrossRef]
15. Wamba, S.F.; Gunasekaran, A.; Akter, S.; Ren, S.J.-F.; Dubey, R.; Childe, S.J. Big data analytics and firm performance. *J. Bus. Res.* **2017**, *70*, 356–365. [CrossRef]
16. Xiang, Z.; Schwartz, Z.; Gerdes, J.H.; Uysal, M. What can big data tell us about hotel guest experience? *Int. J. Hosp. Manag.* **2015**, *44*, 120–130. [CrossRef]
17. Huang, M.H.; Rust, R.T. Artificial intelligence in service. *J. Serv. Res.* **2021**, *24*, 3–19. [CrossRef]
18. Martin, K.D.; Borah, A.; Palmatier, R.W. Data privacy: Effects on customer and firm performance. *J. Mark.* **2017**, *81*, 36–58. [CrossRef]
19. Gursoy, D.; Chi, O.H.; Lu, L.; Nunkoo, R. Consumers' acceptance of artificially intelligent (AI) device use in service delivery. *Int. J. Inf. Manag.* **2019**, *49*, 157–169. [CrossRef]
20. Parasuraman, A.; Zeithaml, V.A.; Berry, L.L. SERVQUAL: A Multiple-Item Scale for Measuring Consumer Perceptions of Service Quality. *J. Retail.* **1988**, *64*, 12–40. Available online: https://www.researchgate.net/publication/200827786_SERVQUAL_A_Multiple-item_Scale_for_Measuring_Consumer_Perceptions_of_Service_Quality (accessed on 12 January 2026).
21. Zeithaml, V.A.; Parasuraman, A.; Malhotra, A. Service Quality Delivery through Web Sites: A Critical Review of Extant Knowledge. *J. Acad. Mark. Sci.* **2002**, *30*, 362–375. [CrossRef]
22. Parasuraman, A.; Zeithaml, V.A.; Malhotra, A. E-S-QUAL: A multiple-item scale for assessing electronic service quality. *J. Serv. Res.* **2005**, *7*, 213–233. [CrossRef]
23. Wirtz, J.; Patterson, P.G.; Kunz, W.; Gruber, T.; Lu, V.N.; Paluch, S.; Martins, A. Brave new world: Service robots in the frontline. *J. Serv. Manag.* **2018**, *29*, 907–931. [CrossRef]
24. Ostrom, A.L.; Parasuraman, A.; Bowen, D.E.; Patrício, L.; Voss, C.A. Service research priorities in a rapidly changing context. *J. Serv. Res.* **2015**, *18*, 127–159. [CrossRef]
25. Marinova, D.; de Ruyter, K.; Huang, M.; Meuter, M.; Challagalla, G. Getting Smart: Learning from Technology-Empowered Frontline Interactions. *J. Serv. Res.* **2017**, *20*, 29–42. [CrossRef]
26. Van Doorn, J.; Mende, M.; Noble, S.M.; Hulland, J.; Ostrom, A.L.; Grewal, D.; Petersen, J.A. Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines. *J. Serv. Res.* **2017**, *20*, 43–58. [CrossRef]
27. Davenport, T.H.; Guha, A.; Grewal, D.; Bressgott, T. How artificial intelligence will change the future of marketing. *J. Acad. Mark. Sci.* **2020**, *48*, 24–42. [CrossRef]
28. Lemon, K.N.; Verhoef, P.C. Understanding customer experience throughout the customer journey. *J. Mark.* **2016**, *80*, 69–96. [CrossRef]
29. McLean, G.; Osei-Frimpong, K. Chat now… Examining the variables influencing the use of online live chat. *Technol. Forecast. Soc. Change* **2019**, *146*, 55–67. [CrossRef]
30. Noor, N.; Rao, S.; Troshani Hill, I. Developing a service quality scale for artificial intelligence service agents. *Eur. J. Mark.* **2022**, *56*, 1301–1336. [CrossRef]
31. Belanche, D.; Casaló, L.V.; Flavián, C.; Schepers, J. Service robot implementation: A theoretical framework and research agenda. *Serv. Ind. J.* **2020**, *40*, 203–225. [CrossRef]

32. Kuo, C.H. Enhancing inbound tourism through the Taiwan outdoor project and AI-enabled chatbot management. In *Proceedings of The International Conference on Electronic Business, ICEB'23, Chiayi, Taiwan, 19–23 October 2023*; Li, E.Y., Chang, S.-I., Yen, B., Eds.; International Conference on Electronic Business (ICEB): Chiayi, Taiwan, 2023; Volume 23, pp. 216–223. Available online: https://aisel.aisnet.org/iceb2023/25 (accessed on 8 January 2026).
33. Rather, R.A. Customer experience and engagement in tourism destinations: The experiential marketing perspective. *J. Travel Res.* **2021**, *60*, 378–391. [CrossRef]
34. Mariani, M.; Baggio, R.; Fuchs, M.; Höepken, W. Business intelligence and big data in hospitality and tourism: A systematic literature review. *Int. J. Contemp. Hosp. Manag.* **2018**, *30*, 3514–3554. [CrossRef]
35. Loureiro, S.M.C.; Guerreiro, J.; Tussyadiah, I. Artificial intelligence in business: State of the art and future research agenda. *J. Bus. Res.* **2021**, *129*, 911–926. [CrossRef]
36. Verhoef, P.C.; Broekhuizen, T.; Bart, Y.; Bhattacharya, A.; Dong, J.Q.; Fabian, N.; Haenlein, M. Digital transformation: A multidisciplinary reflection and research agenda. *J. Bus. Res.* **2021**, *122*, 889–901. [CrossRef]
37. Hoyer, W.D.; Kroschke, M.; Schmitt, B.; Kraume, K.; Shankar, V. Transforming the customer experience through new technologies. *J. Interact. Mark.* **2020**, *51*, 57–71. [CrossRef]
38. Dubois, D.; Prade, H. Possibility theory and its applications: A retrospective and prospective view. In *Proceedings of 12th IEEE International Conference on Fuzzy Systems, 2003. FUZZ '03, St. Louis, MO, USA, 25–28 May 2003*; IEEE: Piscataway, NJ, USA, 2003. [CrossRef]
39. Pappas, N.; Woodside, A.G. Fuzzy-set qualitative comparative analysis (fsQCA): Guidelines for research practice in tourism and hospitality. *Int. J. Contemp. Hosp. Manag.* **2021**, *58*, 102310. [CrossRef]
40. Govindan, K.; Jepsen, M.B. ELECTRE: A comprehensive literature review on methodologies and applications. *Eur. J. Oper. Res.* **2016**, *250*, 1–29. [CrossRef]
41. Herrera, F.; Martínez, L. An approach for combining numerical and linguistic information based on the 2-tuple fuzzy linguistic representation model. *IEEE Trans. Fuzzy Syst.* **2000**, *8*, 746–752. [CrossRef]
42. Yager, R.R. Generalized orthopair fuzzy sets. *IEEE Trans. Fuzzy Syst.* **2017**, *25*, 1222–1230. [CrossRef]
43. Joshi, B.P.; Singh, A.; Bhatt, P.K.; Vaisla, K.S. Interval valued q-rung orthopair fuzzy sets and their properties. *J. Intell. Fuzzy Syst.* **2018**, *35*, 5225–5230. [CrossRef]
44. Aczél, J.; Alsina, C. Characterizations of some classes of quasilinear functions with applications to triangular norms and to synthesizing judgements. *Aequ. Math.* **1982**, *25*, 313–315. [CrossRef]
45. Liu, P.; Wang, P. Some q-rung orthopair fuzzy aggregation operators and their applications to multiple-attribute decision making. *Int. J. Intell. Syst.* **2018**, *33*, 259–280. [CrossRef]
46. Buhalis, D.; Amaranggana, A. Smart tourism destinations: Enhancing tourism experience through ICTs. In *Information and Communication Technologies in Tourism 2014*; Springer: Cham, Switzerland, 2014; pp. 553–564. [CrossRef]
47. Dwivedi, Y.K.; Pandey, N.; Currie, W.; Micu, A. Leveraging ChatGPT and other generative artificial intelligence (AI)-based applications in the hospitality and tourism industry: Practices, challenges and research agenda. *Int. J. Contemp. Hosp. Manag.* **2024**, *36*, 1–12. [CrossRef]
48. López-Naranjo, A.L.; Puente-Riofrio, M.I.; Carrasco-Salazar, V.A.; Erazo-Rodríguez, J.D.; Buñay-Guisñan, P.A. Artificial intelligence in tourism business: A systematic review. *Front. Artif. Intell.* **2025**, *8*, 1599391. [CrossRef] [PubMed]
49. Chotisarn, N.; Phuthong, T. Impact of AI-enabled service attributes on customer satisfaction and loyalty. *Soc. Sci. Humanit. Open* **2025**, *11*, 101306. [CrossRef]
50. Davis, F.D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* **1989**, *13*, 319–340. [CrossRef]
51. Venkatesh, V.; Davis, F.D. A theoretical extension of TAM. *Manag. Sci.* **2000**, *46*, 186–204. [CrossRef]
52. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User acceptance of IT: Toward a unified view. *MIS Q.* **2003**, *27*, 425–478. [CrossRef]
53. Bélanger, F.; Crossler, R.E. Privacy in the digital age: A review of information privacy research. *MIS Q.* **2011**, *35*, 1017–1042. [CrossRef]
54. Dinev, T.; Hart, P. An extended privacy calculus model for e-commerce. *Inf. Syst. Res.* **2006**, *17*, 61–80. [CrossRef]
55. Malhotra, N.K.; Kim, S.S.; Agarwal, J. Internet users' information privacy concerns (IUIPC). *Inf. Syst. Res.* **2004**, *15*, 336–355. [CrossRef]
56. Culnan, M.J.; Armstrong, P.K. Information privacy concerns and procedural fairness. *Organ. Sci.* **1999**, *10*, 104–115. [CrossRef]
57. Lazar, J.; Goldstein, D.F.; Taylor, A. *Ensuring Digital Accessibility Through Process and Policy*; Morgan Kaufmann: Burlington, MA, USA, 2015; ISBN 978-0-12-800646-7.
58. Van Dijk, J. *The Digital Divide*; Polity: Cambridge, UK, 2020; ISBN 978-1-5095-3446-3.
59. Hamari, J.; Koivisto, J.; Sarsa, H. Does gamification work? A literature review. In *Proceedings of the Hawaii International Conference on System Sciences, Waikoloa, HI, USA, 6–9 January 2014*; IEEE: Piscataway, NJ, USA, 2014. [CrossRef]

60. Csikszentmihalyi, M. *Flow: The Psychology of Optimal Experience*; Harper & Row: New York, NY, USA, 1990. Available online: https://www.researchgate.net/publication/224927532_Flow_The_Psychology_of_Optimal_Experience (accessed on 21 January 2026).
61. Novak, T.P.; Hoffman, D.L.; Yung, Y.F. Measuring the customer experience in online environments. *Mark. Sci.* **2000**, *19*, 22–42. [CrossRef]
62. Short, J.; Williams, E.; Christie, B. *Social Presence in Telecommunications*; Wiley: London, UK, 1976; ISBN 0471015814, 9780471015819.
63. Gefen, D.; Straub, D.W. Consumer trust in B2C e-Commerce and the importance of social presence: Experiments in e-Products and e-Services. *Omega* **2004**, *32*, 407–424. [CrossRef]
64. Daft, R.L.; Lengel, R.H. Organizational information requirements and media richness. *Manag. Sci.* **1986**, *32*, 554–571. [CrossRef]
65. Epley, N.; Waytz, A.; Cacioppo, J.T. On seeing human: A three-factor theory of anthropomorphism. *Psychol. Rev.* **2007**, *114*, 864–886. [CrossRef]
66. Nass, C.; Moon, Y. Machines and mindlessness: Social responses to computers. *J. Soc. Issues* **2000**, *56*, 81–103. [CrossRef]
67. Mori, M.; MacDorman, K.F.; Kageki, N. The uncanny valley. *IEEE Robot. Autom. Mag.* **2012**, *19*, 98–100. [CrossRef]
68. Boskovic, S.; Jovcic, S.; Simic, V.; Svadlenka, L.; Dobrodolac, M.; Bacanin, N. A new criteria importance assessment (CIMAS) method in multi-criteria group decision-making: Criteria evaluation for supplier selection. *Facta Univ. Ser. Mech. Eng.* **2025**, *23*, 335–349. [CrossRef]
69. Bouraima, M.B.; Jovcic, S.; Svadlenka, L.; Simic, V.; Badi, I.; Maraka, N.D. An integrated multi-criteria approach to formulate and assess healthcare referral system strategies in developing countries. *Healthc. Anal.* **2024**, *5*, 100315. [CrossRef]
70. Donyatalab, Y.; Farrokhizadeh, E.; Shishavan, S.A.S.; Seifi, S.H. Hamacher aggregation operators based on interval-valued q-rung orthopair fuzzy sets and their applications to decision making problems. In *International Conference on Intelligent and Fuzzy Systems*; Springer: Cham, Switzerland, 2021; Volume 1197. [CrossRef]
71. Jin, C.; Ran, Y.; Zhang, G. Interval-valued q-rung orthopair fuzzy FMEA application to improve risk evaluation process of tool changing manipulator. *Appl. Soft Comput.* **2021**, *104*, 107192. [CrossRef]
72. Kara, K.; Yalçın, G.C.; Çetinkaya, A.; Simic, V.; Pamucar, D. A single-valued neutrosophic CIMAS-CRITIC-RBNAR decision support model for financial performance analysis: A study of technology companies. *Socio-Econ. Plan. Sci.* **2024**, *92*, 101851. [CrossRef]
73. Kara, K.; Yalçın, G.C.; Kaygısız, E.G.; Simic, V.; Örnek, A.Ş.; Pamucar, D. A picture fuzzy CIMAS-ARTASI model for website performance analysis in human resource management. *Appl. Soft Comput.* **2024**, *162*, 111826. [CrossRef]
74. Khan, S.A.R.; Mathew, M.; Dominic, P.D.D.; Umar, M. Evaluation and selection strategy for green supply chain using interval-valued q-rung orthopair fuzzy combinative distance-based assessment. *Environ. Dev. Sustain.* **2022**, *24*, 10633–10665. [CrossRef]
75. Švadlenka, L.; Bajec, P.; Pivtorak, H.; Bošković, S.; Jovčić, S.; Dobrodolac, M. Risk prioritization from the crowd-shipping provider's perspective using the CIMAS method. *Spectr. Eng. Manag. Sci.* **2024**, *2*, 234–246. [CrossRef]
76. Yalçın, G.C. Development of a fuzzy-based decision support system for sustainable tractor selection in green ports. *Facta Univ. Ser. Mech. Eng.* **2025**, *23*, 579–604. [CrossRef]
77. Yalçın, G.C.; Kara, K.; Edinsel, S.; Kaygısız, E.G.; Simic, V.; Pamucar, D. Authentication system selection for performance appraisal in human resource management using an intuitionistic fuzzy CIMAS-ARLON model. *Appl. Soft Comput.* **2025**, *171*, 112786. [CrossRef]
78. Beldad, A.; de Jong, M.; Steehouder, M. How shall I trust the faceless and the intangible? A literature review on the antecedents of online trust. *Comput. Hum. Behav.* **2010**, *26*, 857–869. [CrossRef]
79. Shin, D. The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *Int. J. Hum. Comput. Stud.* **2021**, *146*, 102551. [CrossRef]
80. Collier, J.E.; Bienstock, C.C. Model misspecification: Contrasting formative and reflective indicators for a model of e-service quality. *J. Mark. Theory Pract.* **2009**, *17*, 283–293. [CrossRef]
81. Van der Heijden, H. User acceptance of hedonic information systems. *MIS Q.* **2004**, *28*, 695–704. [CrossRef]
82. Hassenzahl, M. The thing and I: Understanding the relationship between user and product. In *Funology: From Usability to Enjoyment*; Blythe, M.A., Overbeeke, K., Monk, A.F., Wright, P.C., Eds.; Kluwer Academic Publishers: Dordrecht, The Netherlands, 2003; pp. 31–42. [CrossRef]
83. Bitner, M.J.; Brown, S.W.; Meuter, M.L. Technology infusion in service encounters. *J. Acad. Mark. Sci.* **2000**, *28*, 138–149. [CrossRef]
84. Tam, K.Y.; Ho, S.Y. Understanding the impact of web personalization on user information processing and decision outcomes. *MIS Q.* **2006**, *30*, 865–890. [CrossRef]
85. Luo, X.; Tong, S.; Fang, Z.; Qu, Z. Frontiers: Machines vs. humans: The impact of AI chatbot disclosure on customer purchases. *Mark. Sci.* **2019**, *38*, 937–947. [CrossRef]

86. Qiu, L.; Benbasat, I. Evaluating Anthropomorphic Product Recommendation Agents: A Social Relationship Perspective to Designing Information Systems. *J. Manag. Inf. Syst.* **2009**, *25*, 145–182. [CrossRef]
87. Deveci, M.; Pamucar, D.; Gokasar, I.; Pedrycz, W.; Wen, X. Autonomous Bus Operation Alternatives in Ur-ban Areas Using Fuzzy Dombi-Bonferroni Operator Based Decision Making Model. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 15714–15723. [CrossRef]
88. Senapati, T. Approaches to multi-attribute decision-making based on picture fuzzy Aczel–Alsina average aggregation operators. *Comput. Appl. Math.* **2022**, *41*, 40. [CrossRef]
89. Seikh, M.R.; Mandal, U. Some Picture Fuzzy Aggregation Operators based on Frank t-norm and t-conorm: Application to MADM Process. *Informatica* **2021**, *45*, 447–461. [CrossRef]
90. Wang, H.; Zhao, W.; Liu, J.; Feng, L.; Mahmood, T.; Kumar, K. Novel Hamy Mean Aggregation Operators Based on Advanced Operations for T-Spherical Fuzzy Group Decision-Making. *J. Intell. Decis. Mak. Inf. Sci.* **2025**, *2*, 332–365. [CrossRef]
91. Memarpour Ghiaci, A.; Abbasi, M.; Gheidar-Kheljani, J. Enhancing Sustainability in Modular Megaprojects through an SF-CIMAS Approach for Identifying and Prioritizing Supplier Evaluation Criteria. *Res. Prod. Oper. Manag.* **2025**, *16*, 99–130. [CrossRef]
92. Stević, Ž.; Ayhan, E.; Karamaşa, Ç. Earthquake vulnerability analysis based on Fermatean Fuzzy MCDM for reducing uncertainties in disaster management. *Int. J. Environ. Impacts* **2025**, *8*, 1349–1368. [CrossRef]
93. Kou, G.; Yüksel, S.; Eti, S.; Dinçer, H.; Acar, M. Fractal Fuzzy-Based Multi-criteria Assessment of Sustainability in Rare Earth Use for Hydrogen Storage. *Int. J. Comput. Intell. Syst.* **2025**, *18*, 210. [CrossRef]
94. Chen, T.Y. Evolved distance measures for circular intuitionistic fuzzy sets and their exploitation in the tech-nique for order preference by similarity to ideal solutions. *Artif. Intell. Rev.* **2023**, *56*, 7347–7401. [CrossRef]
95. Ecer, F.; Kara, K.; Yalçın, G.C.; Ögel, İ.Y.; Ulutaş, A. Food waste treatment technology assessment in the hospitality industry using a Gaussian intuitionistic fuzzy approach. *J. Clean. Prod.* **2026**, *557*, 148213. [CrossRef]

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