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Enhancing Agri-Food Supply Chain Resilience: A FIT2 Gaussian Fuzzy FUCOM-QFD Framework for Designing Sustainable Controlled-Environment Hydroponic Agriculture Systems

Biset Toprak [1,2,*] and A. Çağrı Tolga [3]

[1] Department of Industrial Engineering, Istanbul Sabahattin Zaim University, Istanbul 34303, Türkiye
[2] Graduate School of Science and Engineering, Galatasaray University, Istanbul 34349, Türkiye
[3] Department of Industrial Engineering, Faculty of Engineering and Technology, Galatasaray University, Istanbul 34349, Türkiye; ctolga@gsu.edu.tr
* Correspondence: biset.toprak@izu.edu.tr

Abstract

Vulnerabilities in conventional agri-food supply chains (CAFSCs) necessitate a shift toward resilient, localized production models. Within the Agri-Food 4.0 landscape, urban Controlled-Environment Hydroponic Agriculture (CEHA) systems address these challenges by shortening supply chains and mitigating climate-induced breakdowns. However, structurally aligning Triple Bottom Line (TBL)-oriented stakeholder needs with complex technical specifications remains a critical challenge in sustainable CEHA system design. To address this challenge, the present study proposes a novel framework integrating the Full Consistency Method (FUCOM) and Quality Function Deployment (QFD) within a Finite Interval Type-2 (FIT2) Gaussian fuzzy environment. This approach systematically translates TBL-oriented priorities into precise engineering specifications, mapping 17 stakeholder needs (SNs) to 30 technical design requirements (TDRs) while capturing linguistic uncertainty and hesitation. The findings reveal a clear strategic focus on environmental and social sustainability. Specifically, high product quality, food safety and traceability, consumer acceptance, and minimization of environmental impacts emerge as the primary drivers of CEHA adoption. The QFD translation identifies scalable IoT infrastructure, sensor maintenance and calibration, and AI-enabled decision support as the most critical TDRs. The framework's reliability and structural robustness were rigorously validated through comprehensive analyses, including Kendall's W test to confirm expert consensus, alongside a Leave-One-Out (LOO) approach, weight perturbations, and a structural evaluation of TDR intercorrelations. These findings provide a scientifically grounded roadmap for designing sustainable, intelligent urban agricultural systems. Ultimately, this framework offers actionable managerial implications for agribusiness stakeholders to bridge strategic TBL-oriented goals with practical engineering, significantly enhancing agri-food supply chain resilience.

Keywords: agri-food supply chain resilience; digital technologies; agri-food 4.0; Internet of Things (IoT); Triple Bottom Line (TBL); Controlled-Environment Hydroponic Agriculture (CEHA); FIT2 Gaussian fuzzy sets; Full Consistency Method (FUCOM); Quality Function Deployment (QFD); House of Quality (HOQ)

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1. Introduction

Agriculture plays a vital role in addressing global food security challenges and contributing to the United Nations Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) [1,2]. Yet the sector currently faces unprecedented pressures. As the global population is projected to reach 9.7 billion by 2050, agricultural yields need to increase per unit area [3]. At the same time, climate change threatens to reduce productivity by up to 10%, and rapid urbanization is shrinking the available arable land [4]. These broad environmental challenges have revealed several shortcomings of traditional, soil-based agriculture and Conventional Agri-Food Supply Chains (CAFSCs) in ensuring food security, particularly for growing urban populations. More importantly, recent global disruptions, such as the COVID-19 pandemic, have highlighted the extreme vulnerability of these centralized, long-distance supply chains. Movement restrictions and border closures disrupted the transport of fresh food, leading to increased food waste, higher export costs, and severe supply shortages in cities [5,6]. Supply chain disruptions lead to reduced productivity, delivery delays, lower customer satisfaction, and a decline in shareholder value [7].

These systemic breakdowns make it clear that shortening the distance between producers and consumers is essential to mitigate the impact of climate change and global disruptions [8]. On the other hand, building supply chain resilience enhances stability and reliability, helping enterprises keep operating smoothly even under deep uncertainty [7]. Supply chain resilience is defined as the ability to prepare for unexpected events, respond effectively to disruptions, and recover by maintaining operations with strong oversight and control [9]. In agri-food supply chains, resilience means not only withstanding external shocks but also managing internal processes effectively and driving targeted technological innovation [10].

To build this kind of resilience, urban Controlled-Environment Agriculture (CEA) systems have emerged as a promising technology. CEA systems—such as smart greenhouses and vertical farms—allow for high-density food production right in urban areas by moving cultivation from outdoor fields to climate-controlled indoor environments [8,11,12]. Among these, vertical farms stand out for their use of vertically stacked layers and soilless growing methods, which maximize space efficiency while drastically cutting water and land use [13–16]. Strategically, CEA offers a resilient, controlled, and localized way to produce food [10]. By shortening transportation distances, these systems reduce waste and provide fresh, high-quality produce year-round [17–19].

Furthermore, integrating Industry 4.0 technologies—such as the Internet of Things (IoT), Artificial Intelligence (AI), Digital Twin (DT), and blockchain—enables real-time monitoring and efficient management, significantly elevating the responsiveness and overall performance of the supply chain [7]. The integration of digital technologies and vertical farming has led to the rise of IoT-based Controlled-Environment Hydroponic Agriculture (CEHA) systems. By embedding smart sensors, automated climate control, and real-time data analytics into soilless farming, CEHA forms the operational core of Agri-Food 4.0. Given the critical role of digital connectivity in modern indoor farming, the term CEHA is hereafter used to denote these advanced, IoT-based vertical hydroponic systems.

Despite these transformative benefits, the broad adoption and long-term success of CEHA systems are still limited by economic, environmental, and technical uncertainties [20]. Many indoor farming initiatives have struggled or failed due to difficulties in technology adoption and scaling operations effectively [19]. Setting up CEHA systems usually demands a large initial investment, sophisticated infrastructure design, and skilled personnel, all of which require carefully customized, context-specific solutions to be successful [21,22].

The literature clearly shows that building resilience in agri-food supply chains (AFSCs) requires a comprehensive understanding of both economic factors and complex

social dynamics [10]. Therefore, successful business models for CEHA systems must balance the Triple Bottom Line (TBL) of sustainability—environmental, economic, and social dimensions—while also ensuring they are operationally feasible [21,23]. Understanding these strategic drivers is essential to moving beyond just following technological trends and securing long-term sustainability [24].

Despite the clear importance of this issue, most existing research on CEA has focused mainly on isolated technological improvements, paying little attention to the strategic factors that influence investment decisions. While studies emphasize the need to develop strong business models [21], they often fall short when it comes to systematically translating TBL-oriented stakeholder needs into practical engineering requirements. Although the conceptualization phase is crucial [25], the current literature lacks specific computational tools to connect these domains during system design. While Full Consistency Method (FUCOM) and Quality Function Deployment (QFD) integrations have proven highly effective in translating stakeholder needs into process and design requirements across various domains, decision-making in agriculture is inherently characterized by high linguistic uncertainty. Both stakeholder evaluations of TBL-oriented priorities and expert assessments of complex system requirements often involve incomplete information and varying degrees of hesitation. Existing FUCOM-QFD integrated applications predominantly rely on Type-1 fuzzy sets, which are insufficient for addressing the deep uncertainty inherent in complex decision problems. Consequently, integrating QFD with FUCOM within an advanced fuzzy environment remains an underexplored area in the literature.

To address these challenges, this research introduces a novel hybrid decision-support framework. The novelty of the study lies in integrating FUCOM and QFD within a Finite Interval Type-2 (FIT-2) Gaussian fuzzy environment. This approach provides a mathematically rigorous bridge for systematically mapping multidimensional, TBL-oriented stakeholder needs (SNs) into precise technical design requirements (TDRs) for CEHA systems, thereby directly enhancing agri-food supply chain resilience.

Accordingly, the study addresses three key research questions:

RQ1: What are the key stakeholder needs for building resilient CEHA systems from a comprehensive TBL perspective?

RQ2: How can these subjective, multi-dimensional priorities be systematically translated into practical technical design requirements under deep linguistic uncertainty?

RQ3: How does the structural alignment of strategic goals and technical requirements inform the design of resilient, scalable, and sustainable agri-food supply chains?

By explicitly bridging the gap between TBL-driven sustainability goals and complex engineering specifications, this study aims to provide a robust and actionable roadmap for policymakers, investors, and system designers to develop resilient urban agri-food networks.

The remainder of this article is organized as follows: Section 2 provides the theoretical background on agri-food supply chain resilience, QFD, and multi-criteria decision-making (MCDM) applications in agriculture. Section 3 details the proposed FUCOM-QFD integrated framework within a FIT2 Gaussian fuzzy environment. Section 4 presents the computational results and validates the model's reliability and structural robustness through comprehensive evaluations. Section 5 discusses the findings and explores the managerial and practical implications for sustainable CEHA design. Finally, Section 6 summarizes the main conclusions, outlines the study's inherent limitations, and highlights future research directions.

2. Literature Review

2.1. Unique Vulnerabilities of Agri-Food Supply Chains (AFSCs)

AFSCs differ fundamentally from conventional industrial supply chains due to their extensive, decentralized network architectures and unique biological constraints. Unlike typical manufacturing logistics, AFSCs are bound by fixed biological production cycles and are highly susceptible to climate-induced disruptions such as weather variability and pest infestations [10,25]. Beyond these structural and environmental challenges, the inherent characteristics of fresh produce—namely seasonality, supply spikes, quality variability, and rapid perishability—make risk management highly complicated [7,25]. Because these products are highly time- and temperature-sensitive, relying on traditional long-distance transportation often results in significant quality deterioration and severe food waste. Recent global disruptions, such as the COVID-19 pandemic, have further highlighted how these inherent structural vulnerabilities amplify the effects of logistical bottlenecks, labor shortages, and market instability [7,26]. This reality underscores the urgent need to strengthen supply chain resilience by maintaining product quality and ensuring a continuous, stable supply despite environmental changes and market fluctuations. To effectively mitigate these combined risks, the industry must transition toward resilient, controlled, and localized production models [6,10]. Ultimately, this strategic shift can be achieved by integrating Agri-Food 4.0 technologies with Short Agri-Food Supply Chains (SAFSCs) within urban agriculture [5,8,21,27].

2.2. SAFSCs and the Role of CEHA Systems

SAFSCs are localized networks that operate with reduced complexity, shorter distances between production and consumption, and rely on direct or intermediate distribution schemes [27]. Unlike conventional agri-food supply chains (CAFSCs), SAFSCs operate within the geographical and social context of a specific community, emphasizing localized, sustainable, and transparent production and consumption practices [28]. By integrating local food production directly into urban or suburban built environments, SAFSCs provide a resilient and sustainable alternative to long CAFSCs. This approach reduces reliance on long-distance logistics and buffers food security against risks from supply chain disruptions and climate variability, offering considerable socio-economic and environmental advantages [27–29].

Figure 1 presents a comparative framework of the transformation from the conventional agri-food supply chains to resilient, short urban food supply chains enabled by CEHA. As illustrated in Figure 1a, the CAFSC has multiple intermediaries and long logistical distances. The majority of emissions associated with this cycle are directly linked to food miles—the distance food travels from the producer to the consumer. Food miles account for an average of 62% of total food emissions from traditional farming [30]. In contrast, Figure 1b demonstrates how an urban CEA system within SAFSCs provides a low-impact system. Because these facilities are located in urban or suburban areas, they eliminate the need for long-distance food transportation. This structural shift significantly reduces travel costs and greenhouse gas (GHG) emissions by limiting food miles, thereby minimizing the carbon footprint of food production [12,31].

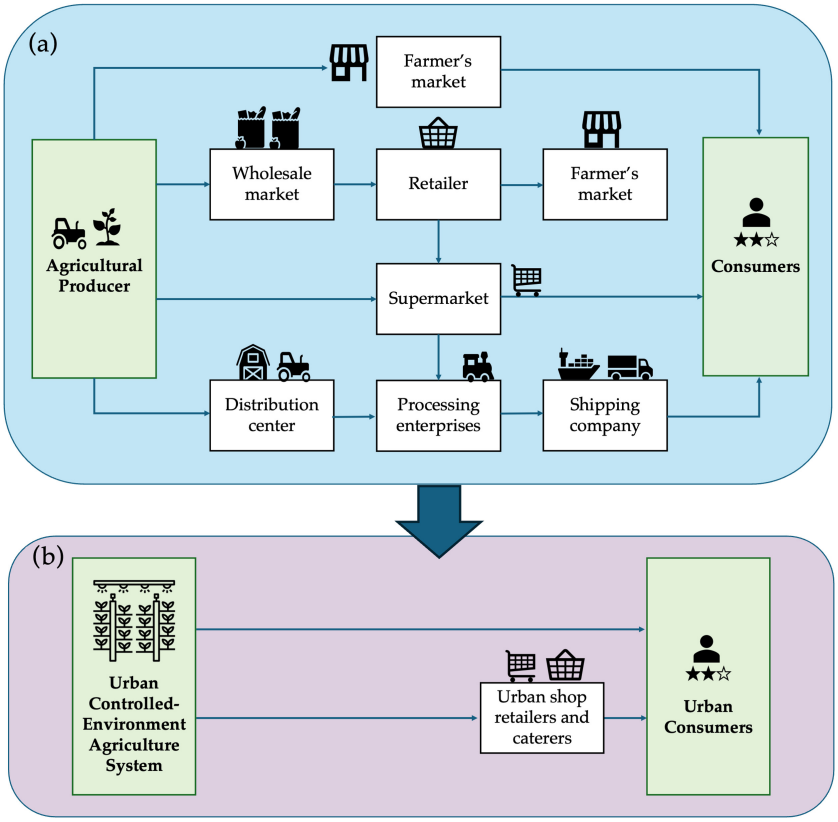


Figure 1. A comparative framework illustrating the transformation from (**a**) the conventional agri-food supply chain with multiple intermediaries and long logistical distances (adapted from [10]); to (**b**) a resilient, short urban food supply chain enabled by CEHA, where production is embedded in the urban location (adapted from [32]).

In this context, CEHA systems serve as strategic solutions by decoupling food production from logistics risks. The physical infrastructure of CEHA provides a foundational layer of structural resilience by insulating crops from climate shocks, seasonality, and external weather, thereby guaranteeing year-round production. However, to fully activate systemic resilience against complex global disruptions, this physical infrastructure must be empowered by Agri-Food 4.0 technologies. Technological advancements and digital transformation provide new tools to strengthen the resilience of agri-food supply chains. Industry 4.0 technologies—such as the IoT, big data, digital twins, and machine learning—improve transparency, traceability, and viability. By leveraging IoT data, these innovations enable rapid response to disruptions, enhance operational efficiency, and significantly reduce supply chain waste [7,33].

It is precisely this integration of digital intelligence with localized physical production (CEHA) that operationalizes the Triple Bottom Line (TBL) dimensions, transforming traditional models into highly resilient SAFSCs. This conceptual synergy manifests across the TBL dimensions as follows:

- Economic Resilience: By excluding unnecessary intermediaries, SAFSCs allow producers to retain a larger share of profits. When enhanced by Agri-Food 4.0 technologies that predictively optimize resource use and prevent system downtime, these CEHA systems extend their service life and contribute to long-term sustainability [34], Consequently, the economic viability and financial stability of urban farming are significantly enhanced [28].
- Social Resilience: Supply chain resilience is fundamentally strengthened through socially embedded relationships. The proximity between producer and consumer fosters

trust, traceability, and a shared understanding of the produce's origin. The combination of localized CEHA production and Agri-food 4.0 guarantees uninterrupted food security for urban populations during crises [28]. Furthermore, real-time disease detection and diagnosis empower farmers to take preventive measures, safeguard their crops, and maximize yields. This technology also opens the door to cultivating a wider variety of exotic and medicinal plants sustainably, ultimately enhancing food security and promoting overall health and wellness [35].

- Environmental Resilience: Localized production drastically reduces fossil fuel dependency and greenhouse gas emissions by minimizing transportation distances [36]. By directly supplying end-users such as urban restaurants, hotels, and local food markets, these systems eliminate long-distance transportation and its associated environmental burdens [37]. Furthermore, AI-enabled control systems continuously analyze real-time IoT sensor data to precisely identify environmental shifts and optimize resource allocation. This intelligent capability improves both reactive and preventive measures within plant factory systems, resulting in enhanced operational performance and environmental resilience [38].

Ultimately, resilience in modern urban agriculture is not merely about surviving disruptions; it is achieved when Agri-Food 4.0 technologies dynamically align CEHA operations with comprehensive TBL-oriented goals [30].

2.3. Strategic Drivers and Stakeholder Needs

The adoption of CEHA is influenced not only by technical innovation but also by strategic and organizational factors. Existing research offers valuable insights into CEHA entrepreneurship and stakeholder expectations. For example, ref. [21] developed a conceptual business model for vertical farm operations, while ref. [39] examined how technology-based firms utilize digital tools to boost efficiency. Advancing the evaluation of these systems, ref. [40] established a comprehensive classification of key performance indicators (KPIs) for vertical farming, and ref. [41] proposed a structural framework to bridge the gap between academic research and practical industry applications.

These studies highlight that successful business models must address specific SNs across the TBL of sustainability—environmental, economic, and social—while ensuring operational feasibility [23,24]. The TBL framework provides a comprehensive qualitative approach for assessing the progress of CEHA and its potential to achieve sustainability. Originally developed as a business strategy, the TBL framework aims to create simultaneous benefits for the company, its consumers, and the environment when effectively implemented [8]. Based on the TBL framework, the main drivers influencing CEHA adoption can be grouped into four core dimensions:

- Environmental Sustainability (ENS): A key driver of urban farming is minimizing the ecological footprint by applying circular economy principles, which focus on reducing waste and promoting resource efficiency [20,42]. Stakeholders demand high energy efficiency in lighting, HVAC, and pumping systems to reduce both environmental impact and costs [21,43]. This focus on energy efficiency must be complemented by careful resource management, particularly of water and nutrients, to minimize waste [44]. Achieving these sustainability objectives relies heavily on integrating real-time monitoring and decision-support systems, enabling data-driven environmental management [16,45].
- Economic Sustainability (ECS): Ensuring economic viability and profitability remains the biggest challenge when compared to traditional farming methods [34]. Stakeholders face high costs and prioritize systems that minimize initial investment costs and operational and maintenance expenses [43,46]. Furthermore, enhancing operational

efficiency and productivity while lowering labor needs through automation is crucial for long-term success [1,22]. To remain adaptable to evolving production demands, these systems must also be designed with modularity and scalability [44].

- Social Sustainability (SS): The successful adoption of CEHA systems depends largely on delivering high product quality, which includes superior taste, freshness, and longer shelf life [21,41]. Ensuring strict food safety and traceability throughout all production stages is essential for building consumer trust and boosting acceptance [22,42]. As a result, the ability to consistently provide high-quality, traceable produce is a vital connection between meeting social expectations and achieving overall system resilience [7].
- Ease of Use and Operational Support (EOS): Given the scarcity of specialized technical expertise within the agricultural workforce, prioritizing system usability through highly intuitive, user-friendly interfaces is a critical necessity [47]. Beyond basic usability, the integration of remote access and mobile control capabilities empowers operators to efficiently manage facilities remotely and respond instantly to critical system alerts [34,48]. Lastly, to ensure operational continuity and mitigate the risks of adopting complex IoT-based systems, stakeholders require comprehensive installation support and training, backed by robust technical guidance and warranty provisions [41,46].

2.4. Technological Enablers and Technical Design Requirements

At the physical and operational levels, modern CEHA facilities rely heavily on advanced resource-optimization technologies. Implementing energy-efficient heating, ventilation, and air conditioning (HVAC) and LED lighting systems is critical for minimizing energy loads while simultaneously optimizing plant growth and micro-climate control [34,38]. Furthermore, transitioning toward closed-loop water systems [42] and integrating renewable energy sources [1,48] directly address the high operational costs and environmental footprints associated with CEHA systems.

IoT enhances CEHA performance by integrating sensors, actuators, and cloud-based platforms for regulating environmental parameters [49,50]. The deployment of a scalable IoT infrastructure and wireless sensor networks (WSNs) equipped with high-quality, low-power sensors ensures continuous, real-time monitoring of light, water, and temperature [20,51]. However, as system complexity scales, establishing data standardization and ensuring component interoperability become essential. Standardized protocols enable diverse devices to communicate securely and reliably [35,44]. Additionally, securing this interconnected architecture requires robust data security measures to protect data confidentiality and integrity from cyber threats [35,38].

This technological integration drives the shift from basic automated control to cognitive, predictive systems. AI-enabled decision support systems provide actionable, real-time insights to optimize resource usage, prevent crop diseases, and dynamically adapt strategies to environmental changes [1,38]. This intelligence reaches its peak in the Digital Twin (DT) framework. A digital product twin simulates and monitors farming processes to predict failures and optimize operations before they occur in the field [42]. DT frameworks have been explored in various contexts, including for tracking subsystems, optimizing resource use efficiency, and the broader agrifood network [19]. Collectively, these technological enablers constitute the TDRs necessary to transform CEA systems into a resilient, data-driven node within the urban supply chain.

2.5. Quality Function Deployment and MCDM Applications in Agriculture

Integrating advanced technological enablers into a sophisticated CEA architecture is a highly complex task that requires decision-makers to balance numerous interdependent, often conflicting criteria, such as cost, energy efficiency, and scalability. Therefore, conducting an integrative assessment of different urban agriculture types through MCDM method can support strategic decision-making by identifying the most suitable CEA systems that effectively address diverse ecological, social, and economic demands within the urban food supply system [52]. To navigate this complexity, within the domain of CEA, MCDM approaches have been extensively utilized. However, existing applications predominantly focus on technology selection and performance evaluation rather than system design. For strategic planning, Kamonpatana et al. [53] used a modified Fuzzy Delphi Method to identify critical success factors, yet the broader literature remains heavily skewed toward assessing existing alternatives. For instance, Tolga et al. [54] employed fuzzy EDAS, and Tolga and Başar [55] used EDAS and TODIM methods to evaluate vertical farming structures (e.g., containers vs. warehouses). Furthermore, Büyüközkan and Uztürk [56] and Büyüközkan et al. [57] evaluated vertical farming technologies. Tolga and Başar [4] compared traditional versus IoT-based automated systems using WEDBA and MACBETH methods. Nadal et al. [58] applied the AHP method specifically to evaluate rooftop greenhouses. Alem et al. [59] and Alnaqbi and Aracı [60] have extended these evaluations to automation levels and comparative sustainability assessments of hydroponic systems, respectively. John and Artmann [52] developed a framework that uses the Analytic Hierarchy Process (AHP) to evaluate the environmental, social, and economic impacts of urban agriculture.

While these studies provide valuable insights, establishing a CEHA system and developing resilient urban agriculture remains practically challenging. System designers must balance several complex factors simultaneously, such as crop quality, system scalability, and the integration of digital technologies [53]. Despite the clear advantages of CEHA, the sector faces significant barriers to widespread adoption, such as high initial capital costs, energy intensity, and a lack of standardized evaluation indicators. These complexities necessitate a robust decision-support framework to structurally align strategic TBL-oriented needs with technical implementations. To achieve this, QFD emerges as a highly effective method to align these expectations with precise engineering requirements.

2.5.1. Quality Function Deployment

QFD has been extensively applied across the agricultural domain to translate stakeholder expectations into actionable design and process requirements. For example, Castiblanco Jimenez et al. [61] integrated QFD with TAM to assess factors shaping the adoption of agricultural innovations. Ayyildiz et al. [62] used an interval-valued Pythagorean fuzzy AHP–QFD approach to align customer expectations with cultivation practices in Türkiye's hazelnut industry, while Singh and Agrawal [63] employed QFD to design a customer-oriented framework for Weather Index Insurance. Within agricultural supply chains, QFD has been combined with TOPSIS [64], grey relational analysis [65], and DEMATEL to align sustainable customer expectations with technical supply chain drivers. Ocampo Jimenez and Baeza Serrato [66] applied QFD to match municipal agricultural services with farmers' needs, and Büyüközkan and Uztürk [67] investigated interactions between digitalization and sustainability using a two-stage QFD framework. Taken together, these studies underscore QFD's wide-ranging and robust applicability in advancing agricultural systems by enhancing customer satisfaction, supporting technology adoption, and improving production and service processes.

However, traditional crisp QFD models struggle to handle the inherent linguistic imprecision and hesitation in expert evaluations. To improve the reliability of the data collection process, Bottani and Rizzi [68] introduced fuzzy logic into the HOQ. A critical preliminary step in constructing this fuzzy HOQ is accurately determining the relative importance of SNs. Evaluating the relative priority of these needs ensures that stakeholder expectations are effectively translated into design requirements [67].

Building on this wide scope of applications, integrating QFD with MCDM techniques provides a structured, stakeholder-oriented approach to addressing complex decision problems. However, a review of the existing literature reveals that, in the agricultural context, QFD is typically combined with conventional criteria weighting methods, such as AHP and DEMATEL. AHP requires a large number of pairwise comparisons, placing a significant cognitive burden on decision-makers (DMs) and making it challenging to maintain mathematical consistency in complex models. In contrast, the DEMATEL method lacks an inherent consistency measure to validate DM judgments. To overcome these methodological limitations, FUCOM has recently gained prominence due to its simplicity, reduced computational complexity, and high reliability in criterion weighting [69].

2.5.2. Full Consistency Method

The FUCOM has been widely adopted in recent literature, primarily for determining the priority weights of criteria within hybrid MCDM frameworks. A prominent area of application is sustainable supplier selection, where FUCOM has been successfully integrated with various methods such as COPRAS [70], WASPAS [71], SAW [72], and MAIRCA [73]. Beyond the supply chain domain, the versatility of FUCOM has been demonstrated in complex location and site-selection problems, including wind farms [74], logistics centers [75], and landfill sites [76]. Furthermore, its applicability extends across highly diverse operational domains, ranging from manufacturing to human resource management [77–81].

Specifically, FUCOM–QFD integrations have proven highly effective in translating stakeholder WHATs into technical HOWs across various sectors, including healthcare [82,83], pharmaceuticals [84], energy [85], and eco-tourism [86]. These studies collectively demonstrate that fuzzy QFD, supported by the FUCOM weighting, effectively captures the vagueness in DMs' assessments while ensuring high consistency.

Based on the main steps of the FUCOM [69], Pamučar and Ecer [87] extended FUCOM with Type-1 fuzzy sets for determining weights as accurately as possible under fuzziness to model real-life problems. In recent years, fuzzy extensions of FUCOM have been successfully integrated with various weighting and ranking methods for evaluating alternative fuel vehicle selection, traffic management, road safety, and occupational risk evaluation [88–91].

2.6. Research Gap and Contributions

From a practical perspective, existing research on CEHA systems has predominantly focused on isolated technological optimizations, paying limited attention to the strategic factors that govern investment decisions. While studies highlight the importance of business model development, they consistently fall short of structurally translating TBL-oriented stakeholder needs into concrete engineering requirements. Although the conceptualization phase is the critical transition point from understanding stakeholder expectations to identifying technical parameters [92], the literature currently lacks specific computational tools to align these domains during system design. Misaligned engineering decisions often fail to meet the dynamic demands of urban CEHA systems, posing a severe risk to the resilience of the agri-food supply chain.

Second, from a methodological perspective, decision-making in such multi-stakeholder agricultural environments is characterized by high, often linguistic, uncertainty. While the structural inefficiencies of conventional weighting methods are effectively resolved by adopting FUCOM, a critical limitation remains in modeling the inherent vagueness in human judgments. Both stakeholder evaluations of TBL-oriented priorities and expert assessments of complex system requirements often involve incomplete information and varying degrees of hesitation. Existing FUCOM-QFD integrated applications predominantly rely on standard Type-1 fuzzy sets introduced by Zadeh [93], which are constrained to precise, crisp membership degrees and are thus insufficient for addressing the deep uncertainty inherent in such complex decision problems. Consequently, integrating QFD with FUCOM within an advanced fuzzy environment remains an underexplored area in the literature.

To overcome these limitations, the present study introduces an integrated FUCOM-QFD framework within a FIT2 Gaussian fuzzy environment. This novel approach inherently models the Footprint of Uncertainty (FOU), providing a rigorous mathematical representation of DMs' and experts' linguistic uncertainty and hesitation. As the first study to operationalize this methodology in the agri-food domain, this integration ensures that the final TDRs for CEHA systems are not only technologically advanced but also strategically aligned and mathematically robust against the complexities of the Agri-Food 4.0 era.

3. Materials and Methods

Given the multidisciplinary and complex nature of the CEA and Agri-Food 4.0 systems, this study employs a multi-stage hybrid decision-support framework. The structural workflow of the proposed methodology, which integrates FUCOM and QFD methods within a FIT2 Gaussian fuzzy environment, is illustrated in the flowchart in Figure 2.

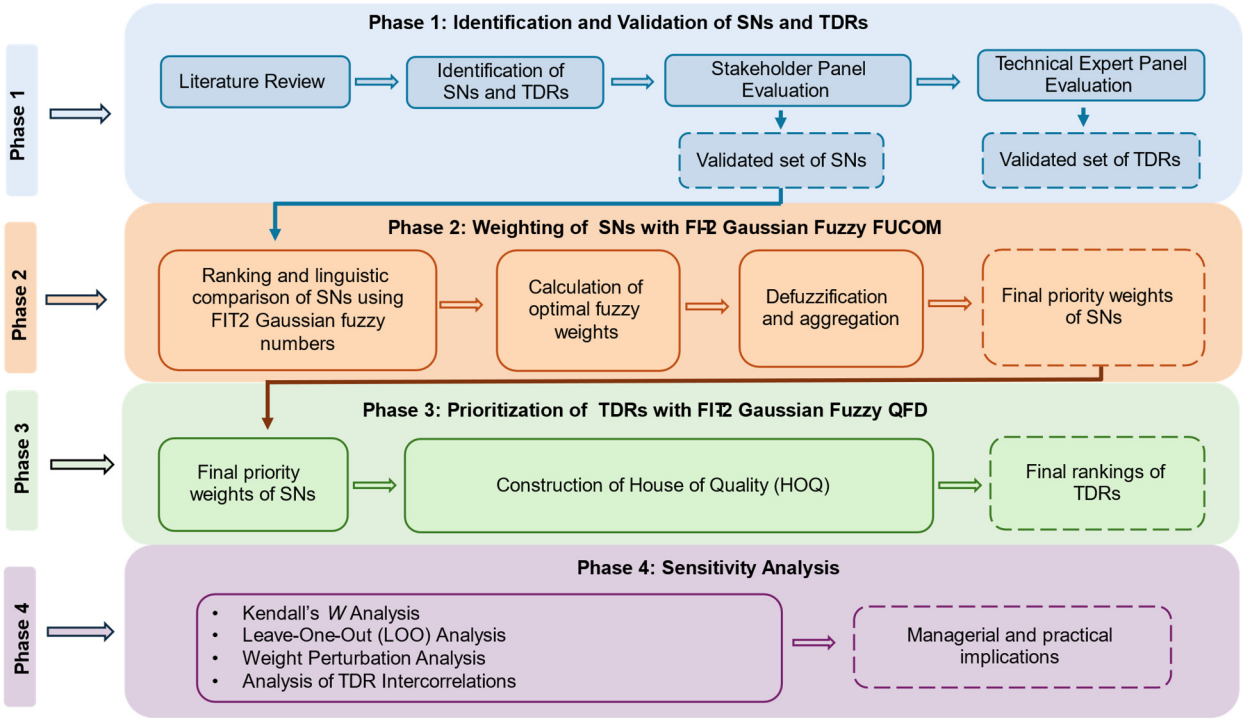


Figure 2. The proposed FUCOM-QFD framework within a FIT2 Gaussian fuzzy environment.

To ensure the reliability of this framework, considerable attention was dedicated to establishing stakeholder and expert panels with diverse and complementary backgrounds [94]. Recognizing that research in the agricultural sector frequently relies on

non-probability sampling techniques, this study employs a purposive sampling approach. This strategy was chosen based on a rigorous set of criteria supported by similar studies [26,95]. Grounded in the expert-based evaluation literature, which suggests that small groups of three to five authoritative individuals can provide valid and reliable insights in specialized fields, sufficient to ensure methodological validity and reliability in domain-specific contexts, this study emphasizes the depth and quality of expertise over panel size [94,96].

3.1. Expert Panels and Model Development

Accordingly, in Phase I, the panel selection process followed two rigorous criteria: (1) Domain Experience—each panel member must have a minimum of ten years of active professional experience in relevant areas; (2) Professional/Academic Qualification—each panel member must hold at least an undergraduate degree in a related discipline.

In accordance with these criteria, the DM panel (Table 1) was selected to identify and validate stakeholder seeds. While their professional backgrounds differ, together they bring comprehensive expertise that covers the critical dimensions of Agri-Food 4.0 business models.

Table 1. Demographic profile of the stakeholder panel.

DM ID	Education Level	Profession	Expertise Areas	Experience (Years)
DM1	Bachelor's	Business Manager	Sales & Marketing	10
DM2	PhD	Financial Analyst	Central Banking, Finance	25
DM3	Bachelor's	Entrepreneur	Soilless Agriculture, Hydroponics	12
DM4	Bachelor's	Engineer	Systems Engineering	15

The second panel (Table 2) consists of four senior technical experts (TEs) responsible for translating the prioritized SNs into practical TDRs. These experts, chosen for their specialized academic and industry experience, were selected to tackle the complex technological, mechatronic, and data-driven challenges inherent in CEHA systems. This purposive sampling strategy ensured that TEs had both sector-specific expertise and practical experience with CEA systems, enhancing the reliability and validity of the study's findings.

Table 2. Demographic background of technical experts.

Expert ID	Education Level	Profession	Position	Expertise Areas	Experience (Years)
TE1	PhD	Academic	Associate Professor	Information Technologies, Mechatronic Systems	30
TE2	Bachelor's	Mechanical Engineer	Manager	Plant Cultivation Systems	30
TE3	PhD	Academic	Assistant Professor	Mechatronics, Machine Learning, Embedded Systems	22
TE4	PhD	Academic	Assistant Professor	Sensor Nodes	15

Following the construction of the panels, the criteria were developed through a strict sequential process. In accordance with fundamental QFD methodology, the SNs (WHATs) were defined first, serving as the foundational baseline to systematically determine the

TDRs (HOWs). As illustrated in Phase I of the proposed methodology (Figure 2), first, a preliminary pool of potential SNs was compiled based on the background literature. This initial list was then presented to the DM panel (Table 1) through structured discussions. During this session, overlapping needs were merged, and terminology was adapted to reflect the TBL-focused realities of urban farming, yielding the finalized, validated set of SNs.

Once the SNs were established, the process moved to determining the TDRs required to fulfill them. An initial set of potential TDRs was extracted from recent Agri-Food 4.0 and CEHA literature. Subsequently, the TE panel (Table 2) evaluated these parameters. The TEs rigorously examined these parameters to ensure they were technologically feasible, measurable, and directly capable of satisfying the validated SNs. A criterion was retained only if the experts reached a consensus on its critical importance. This rigorous, sequential filtering process yielded highly contextualized sets of WHATs and HOWs used in the subsequent QFD framework.

With the validation phase complete, the finalized SNs and TDRs were mapped into a unified decision model (Figure 3), aligning the 17 SNs—hierarchically grouped into the core TBL dimensions alongside essential operational criteria (Ease of Use and Operational Support)—with the comprehensive set of 30 TDRs. Such structured mapping serves as a crucial foundation for bridging the gap between strategic sustainability objectives, practical system usability, and operational engineering specifications, providing a rigorous baseline for the subsequent fuzzy evaluations. Detailed definitions and supporting literature for all SNs and TDRs are provided in Appendix A (Tables A1 and A2, respectively).

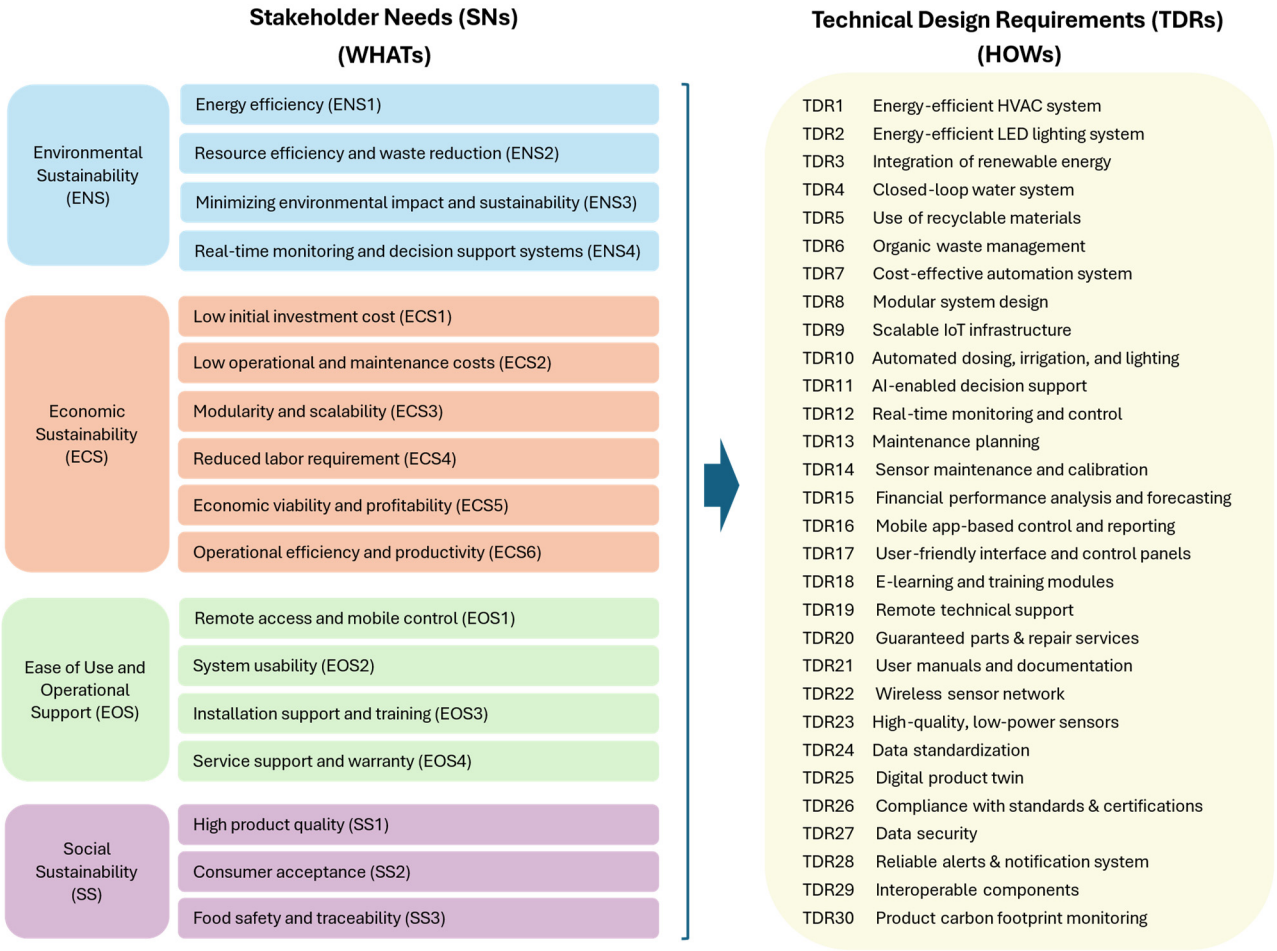


Figure 3. The structure of the proposed decision model: Bridging the extended TBL-oriented SNs with TDRs.

3.2. Preliminaries of Finite Interval Type-2 (FIT2) Gaussian Fuzzy Sets

Type-2 fuzzy sets, introduced by Zadeh [97], are characterized by fuzzy membership functions where the degree of membership is itself fuzzy. This third dimension provides additional design degrees of freedom to address higher levels of uncertainty and vagueness that conventional Type-1 sets struggle to model effectively. However, their standard forms often entail high computational complexity, limiting their practical application to complex problems [91,92]. Interval-valued Type-2 (IT2) fuzzy sets have become the most preferred representation in real-world applications due to their computational tractability.

A graphical illustration of an IT2 Gaussian fuzzy set is presented in Figure 4, where the shaded area represents the FOU, the region bounded between the upper and lower membership functions. Furthermore, the integration of Gaussian functions better reflects real-world phenomena. By keeping the Gaussian functions within a finite sigma limit, FIT2 Gaussian fuzzy numbers—introduced by Tolga et al. [98]—provide a rigorous and highly practical mathematical representation of the hesitation inherent in human decision-making. Although originally validated for strategic medical technology selection in its initial application, this robust framework is leveraged in our study to more effectively capture the imprecise judgments and vague comparisons inherent in the complex CEHA system design.

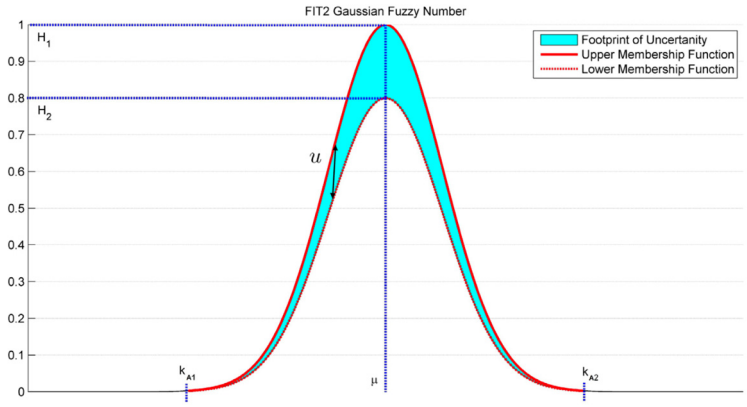


Figure 4. Representation of an IT2 Gaussian fuzzy set.

A FIT2 Gaussian fuzzy number is defined as follows:

$$\widetilde{A} = (k_{A1}, m_A, k_{A2}; H_{A^U}, H_{A^L}) \quad (1)$$

The detailed explanation of the core concepts and operational rules of FIT2 Gaussian fuzzy numbers are provided in Appendix B.

3.3. FUCOM

Introduced by Pamučar et al. [69], FUCOM is a highly effective MCDM technique used to determine the priority weights of criteria. It was selected for this study for its clear practical advantages over traditional weighting methods. It supports highly flexible evaluation scales (both integer and decimal) and employs a robust algorithm that mathematically validates the model's reliability by calculating the Deviation from Full Consistency (DFC). By enforcing strict transitivity conditions with $(n-1)$ pairwise comparisons, FUCOM minimizes computational effort while guaranteeing highly consistent expert evaluations [74,75]. To prioritize the identified SNs, the FUCOM procedure is executed as follows [69,88].

Step 1: Rank the criteria. The evaluation criteria $C = \{C_1, C_2, \ldots, C_n\}$ are ranked by DMs according to their expected significance. The highest rank is assigned to the criterion

anticipated to have the largest weight coefficient, with subsequent ranks assigned to criteria of decreasing significance.

$$C_{i(1)} > C_{i(2)} > \cdots > C_{i(k)} \tag{2}$$

where k represents the rank of the criterion.

Step 2: Compare the criteria using the FIT2 Gaussian linguistic scale. The comparative significance of the criteria is determined by comparing the first-ranked (most important) criterion with each of the remaining criteria, performing pairwise comparisons. The linguistic scales utilized for DM evaluations are based on the fuzzy scale proposed by Pamučar and Ecer [87] and subsequently expanded by Gölcük et al. [90]. To model these evaluations within a FIT2 Gaussian fuzzy environment, the membership function parameters were integrated using the validated scales from Tolga et al. [98]. These parameters were rigorously tested to ensure mathematical feasibility within the FUCOM optimization framework, consistently yielding high-consistency solutions. Finally, the nine-level linguistic scale presented in Table 3 was developed to define the linguistic terms and their corresponding FIT2 Gaussian fuzzy numbers. Based on the defined significance of criteria, the fuzzy comparative significance $\left(\varphi_{k/(k+1)}\right)$ is determined by using Equation (3).

$$\tilde{\varphi}_{k/(k+1)} = \frac{\omega_{C_{i(k+1)}}}{\omega_{C_{i(k)}}} = \frac{\left(\omega^{k_{i1}}_{C_{i(k+1)}}, \omega^{\mu_{Ai}}_{C_{i(k+1)}}, \omega^{k_{i2}}_{C_{i(k+1)}}; \omega^{H_U}_{C_{i(k+1)}}, \omega^{H_L}_{C_{i(k+1)}}\right)}{\left(\omega^{k_{i1}}_{C_{i(k)}}, \omega^{\mu_{Ai}}_{C_{i(k)}}, \omega^{k_{i2}}_{C_{i(k)}}; \omega^{H_U}_{C_{i(k)}}, \omega^{H_L}_{C_{i(k)}}\right)} \tag{3}$$

Table 3. FIT2 Gaussian fuzzy linguistic scale for evaluating SNs.

Linguistic Terms	FIT2 Gaussian Fuzzy Numbers (k_{i1}, μ_{Ai}, k_{i2}; $H_{Ai}{}^{U}$, $H_{Ai}{}^{L}$)
Equally Important (EI)	(1.5, 3, 4.5; 1, 0.9)
Weakly Important (WI)	(3, 4.5, 6; 1, 0.9)
Moderate Important (MI)	(4.5, 6, 7.5; 1, 0.9)
Above Moderate Important (AMI)	(6, 7.5, 9; 1, 0.9)
Quite Important (QI)	(7.5, 9, 10.5; 1, 0.9)
Quietly Above Important (QAI)	(9, 10.5, 12; 1, 0.9)
Very Important (VI)	(10.5, 12, 13.5; 1, 0.9)
Very Very Important (VVI)	(12, 13.5, 15; 1, 0.9)
Extremely Important (EXI)	(13.5, 15, 16.5; 1, 0.9)

Step 3. Calculate the optimal fuzzy weights: The resultant weights must satisfy two fundamental conditions, as defined in Equations (4) and (5).

Condition 1: The ratio of weights must match the comparative significance:

$$\frac{w_k}{w_{k+1}} = \varphi_{k/(k+1)} \tag{4}$$

Condition 2: The condition of mathematical transitivity must be satisfied:

$$\frac{w_k}{w_{k+2}} = \varphi_{k/(k+1)} \bigotimes \varphi_{k+1/(k+2)} \tag{5}$$

After satisfying these conditions, the optimal fuzzy weight coefficients are obtained by minimizing the deviation parameter χ. The resulting fuzzy linear programming model is formulated as follows:

$$min\ \chi$$

s.t.

$$\left| w_k - w_{k+1} \bigotimes \varphi_{k/(k+1)} \right| \leq \chi, \forall i \tag{6}$$

$$\left| w_k - w_{k+2} \bigotimes \varphi_{k/(k+1)} \bigotimes \varphi_{(k+1)/(k+2)} \right| \leq \chi, \forall i \tag{7}$$

$$\sum_{j=1}^{m} w_i = 1, \forall i, \tag{8}$$

$$w_i^{k_{i1}} \leq w_i^{\mu_{Ai}} \leq w_i^{k_{i2}}, \tag{9}$$

$$w_i^{k_{i1}} \geq 0, \forall i \tag{10}$$

$$i = 1, 2, \ldots, m$$

where $w_i = w_i^{k_{i1}}, w_i^{\mu_{Ai}}, w_i^{k_{i2}}, w_i^{H_U}, w_i^{H_L}$ and $\varphi_{k/(k+1)} = (\varphi_{k/(k+1)}^{k_{i1}}, \varphi_{k/(k+1)}^{\mu_{Ai}}, \varphi_{k/(k+1)}^{k_{i2}}, \varphi_{k/(k+1)}^{H_U}, \varphi_{k/(k+1)}^{H_L})$.

Step 5: Defuzzify optimal weights and rank the SNs. Once the linear model is solved, the resulting optimal fuzzy weights are defuzzified using Equations (A8)–(A13). Subsequently, the SNs are ranked in descending order based on their final crisp weights (w_i). Building on these established priorities, the framework directly proceeds to the QFD phase.

3.4. QFD

QFD is a systematic methodology introduced by Yoji Akao and Shigeru Mizuno in the late 1960s and first implemented by Mitsubishi in 1972 [84,86]. Its primary function is to translate customer needs into technical attributes—or, within the context of this study, to translate strategic TBL-oriented SNs into specific TDRs. By integrating stakeholder expectations into the engineering design process, QFD enhances customer satisfaction, facilitates informed decision-making, and significantly reduces development time and costs by minimizing design-related errors [99].

The core analytical tool of this methodology is the House of Quality (HOQ), which generates a mathematically prioritized list of technical actions [83,100]. The prioritization depends on the relationship strength between WHATs and HOWs, as well as the intercorrelations (the roof matrix) among the HOWs themselves [85].

In this step, the QFD methodology is integrated into the FIT2 Gaussian fuzzy environment. A representation of the HOQ structure is presented in Figure 5.

The methodological procedure is applied as follows [82].

Step 1: Construct the relationship matrix. The relationship matrix between SNs $(i = 1, \ldots, m)$ and TDRs $(j = 1, \ldots, n)$ is established. The degree of the relationships is assessed by DMs using the linguistic scale presented in Table 4. Each expert evaluates 17×30 matrix using the linguistic scale, and the corresponding FIT2 Gaussian fuzzy numbers are placed in the central part of the HOQ, forming the relationship coefficients $(\widetilde{R}_{ij})$. These coefficients represent the degree to which a specific TDR addresses an SN.

Table 4. Fuzzy scale for assessing the relationship matrix.

Degree of Relationship	FIT2 Gaussian Fuzzy Numbers (k_{i1}, μ_{Ai}, k_{i2}; $H_{Ai}{}^{U}$, $H_{Ai}{}^{L}$)
No (N)	(0, 0, 0; 1, 0.9)
Less Weak (LW)	(0, −0.1, 0.3; 1, 0.9)
Weak (W)	(0.1, 0.3, 0.5; 1, 0.9)
Moderate (M)	(0.3, 0.5, 0.7; 1, 0.9)
Strong (S)	(0.5, 0.7, 0.9; 1, 0.9)
Very Strong (VS)	(0.7, 0.9, 1; 1, 0.9)

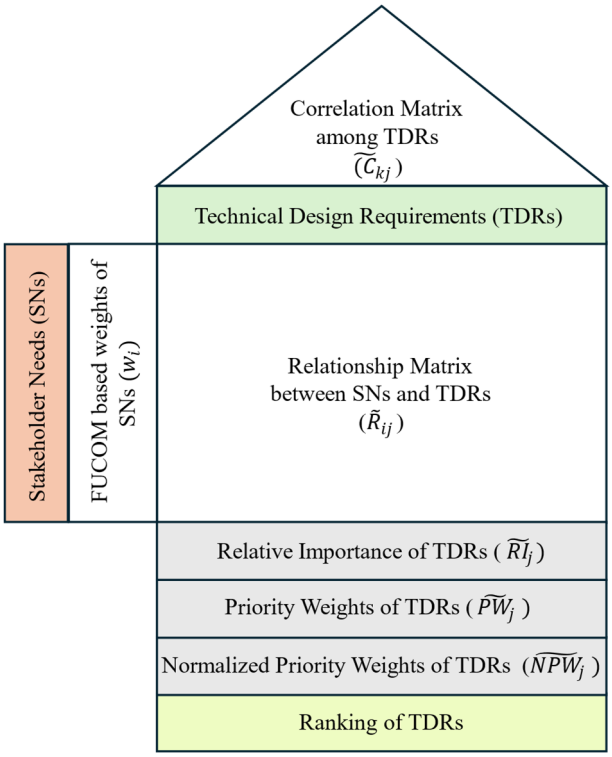


Figure 5. The House of Quality.

Step 2: Compute the relative importance of TDRs. The Relative Importance ($\widetilde{RI}_j$) of each TDR is computed by

$$\widetilde{RI}_j = \sum_{i=1}^{m} w_i \otimes \widetilde{R}_{ij}, j = 1, \ldots, n \quad (11)$$

Step 3: Construct the correlation matrix. The intercorrelations among the TDRs are assessed by experts using the FIT2 linguistic scale presented in Table 5. Each expert evaluates a 30 × 30 intercorrelation matrix using the provided linguistic scale. These individual evaluations are averaged, and the resulting aggregated FIT2 Gaussian fuzzy numbers are placed into the roof of the HOQ to form intercorrelation coefficients $\widetilde{C}_{kj}$,(where $k \neq j$). The FIT2 Gaussian fuzzy scales utilized to assess the relationships and intercorrelations, as presented in Tables 4 and 5, were adopted from the foundational frameworks of Bottani and Rizzi [68] and Bottani [101]. These linguistic assessments are subsequently translated into FIT2 Gaussian numbers using the validated parameters from Tolga et al. [98].

Table 5. Fuzzy scale for assessing the correlation matrix.

Degree of Correlation	FIT2 Gaussian Fuzzy Numbers (k_{i1}, μ_{Ai}, k_{i2}; H_{Ai}^{U}, H_{Ai}^{L})
Very High Negative (VHN)	(−1, −0.9, −0.7; 1, 0.9)
High Negative (HN	(−0.9, −0.7, −0.5; 1, 0.9)
Moderate Negative (MN)	(−0.7, −0.5, −0.3; 1, 0.9)
Low Negative (LN)	(−0.5, −0.3, −0.1; 1, 0.9)
No (N)	(0, 0, 0; 1, 0.9)
Low Positive (LP)	(0.1, 0.3, 0.5; 1, 0.9)
Moderate Positive (MP)	(0.3, 0.5, 0.7; 1, 0.9)
High Positive (HP)	(0.5, 0.7, 0.9; 1, 0.9)
Very High Positive (VHP)	(0.7, 0.9, 1; 1, 0.9)

Step 4: Determine the final priority weights. The priority weight $(\widetilde{PW}_j)$ of each TDR is calculated by

$$\widetilde{PW}_j = \widetilde{RI}_j \bigoplus \sum_{k=j} \widetilde{C}_{kj} \bigotimes \widetilde{RI}_k \quad (12)$$

where $\widetilde{C}_{kj}$ represents the correlation coefficient between TDR_k and TDR_j.

Step 5: Normalize the priority weights. To facilitate comparison, the fuzzy priority weights are normalized by dividing each $\widetilde{PW}_j$ by the maximum value of $\widetilde{PW}_j$. To find the maximum value of $\widetilde{PW}_j$, each $\widetilde{PW}_j$ value is defuzzied using Equations (A8)–(A13).

Step 6: Defuzzify the normalized priority weights and rank the TDRs. The normalized fuzzy weights $(\widetilde{NPW}_j)$ are then defuzzified using Equations (A8)–(A13). Finally, all TDRs are ranked in descending order of their final crisp values.

4. Results

4.1. Prioritization of Stakeholder Needs

The FIT2 Gaussian fuzzy FUCOM was applied to derive consistent and reliable weights for the SNs. This step ensured that uncertainty and subjectivity in DM's evaluations were minimized through the consistency validation mechanism of FUCOM. The phase associated with FUCOM started with ranking of SNs as defined in Equation (2) and is followed by pairwise comparisons among four DMs (see Table 1) using the linguistic scale presented in Table 3. These linguistic assessments were then represented as corresponding FIT2 Gaussian fuzzy numbers, and the fuzzy comparative significance of the criteria was calculated using Equation (3). Once the conditions in Equations (4) and (5) were fulfilled, the resulting linear model was solved in LINGO 20.0. Finally, the resulting weights were defuzzified using Equations (A8)–(A13). This procedure was repeated for the main and sub-criteria for each DM. The individual results were then aggregated via the arithmetic mean to establish a consensus ranking. Global weights of sub-criteria were subsequently derived by multiplying the main criteria's weights by their respective sub-criteria's local weights. The results for the FIT2 Gaussian fuzzy FUCOM application are presented in Table 6, the criterion with the highest weight is ranked first.

Table 6. Final weights of stakeholder needs.

Main Criteria	Main Criteria Weights	Rank	Sub-Criteria	Sub-Criteria Weights	Rank
Environmental Sustainability (ENS)	0.2629	1	Energy efficiency (ENS1)	0.0677	5
			Resource utilization efficiency and waste reduction (ENS2)	0.0648	6
			Minimization of environmental impacts and sustainability (ENS3)	0.0690	4
			Real-time monitoring and decision support systems (ENS4)	0.0615	8
Economic Sustainability (ECS)	0.2551	3	Low investment cost (ECS1)	0.0459	14
			Low operation and maintenance cost (ECS2)	0.0338	17
			Modular expandability (ECS3)	0.0391	15
			Low labor requirement (ECS4)	0.0351	16
			Financial sustainability and profitability (ECS5)	0.0486	12
			Operational efficiency and productivity (ECS6)	0.0527	10
Ease of Use and Operational Support (EOS)	0.2190	4	Remote access and mobile control (EOS1)	0.0604	9
			System usability (EOS2)	0.0621	7
			Installation and training support (EOS3)	0.0477	13
			Service and warranty support (EOS4)	0.0488	11

Table 6. *Cont.*

Main Criteria	Main Criteria Weights	Rank	Sub-Criteria	Sub-Criteria Weights	Rank
Social Sustainability (SS)	0.2626	2	High product quality (SS1)	0.0911	1
			Consumer acceptance (SS2)	0.0812	3
			Food safety and traceability (SS3)	0.0901	2

4.2. Translating Stakeholder Needs into Technical Design Requirements

In this phase, the QFD methodology is utilized the HOQ to systematically evaluate both the complex relationships between SNs and TDRs, and the intercorrelations among the TDRs (the HOQ roof). The prioritized SN weights—derived from the FIT2 Gaussian fuzzy FUCOM process in Phase II—serve as the primary input for this evaluation. To anchor the final technical requirements in the TBL-oriented strategic objectives, these weighted SNs are translated into corresponding TDRs within a FIT2 Gaussian fuzzy environment.

As a practical illustration of this mechanism, consider a highly prioritized SN, such as high product quality (SS1), obtained from the FUCOM stage. The model evaluates the extent to which a specific TDR, such as AI-enabled decision support (TDR11), contributes to fulfilling this need. The fuzzy logic mathematically integrates the SN's priority weight, the SN-TDR relationship strength, and the TDR intercorrelations to produce the final ranking. To execute this systematically, the four TEs (see Table 2) evaluated these relationships and intercorrelations using the predefined linguistic scales in Tables 4 and 5, respectively.

After aggregating the expert evaluations via the arithmetic mean, the relative importance ($\widetilde{RI}_j$) and priority weights ($\widetilde{PW}_j$) of the TDRs were calculated using Equations (11) and (12), respectively. The normalized weights ($\widetilde{NPW}_j$) were then computed by dividing each $\widetilde{PW}_j$ by the maximum priority weight. To identify this maximum value, all $\widetilde{PW}_j$ values were defuzzified using Equations (A8)–(A13). Following normalization, the $\widetilde{NPW}_j$ values were defuzzified to yield the final crisp values. Consequently, the TDRs were ranked by their descending crisp values, providing a prioritized roadmap for system design. The final ranking of the TDRs is presented in Table 7, while the roof and central matrix of the HOQ are provided in Appendix C (see Figures A1 and A2, respectively).

Table 7. Final ranking of the TDRs.

Code	Technical Design Requirements	Crisp Values	Rank
TDR9	Scalable IoT infrastructure	0.6684	1
TDR14	Sensor maintenance and calibration	0.6683	2
TDR11	AI-enabled decision support	0.6658	3
TDR8	Modular system design	0.6614	4
TDR24	Data standardization	0.6511	5
TDR13	Maintenance planning	0.6469	6
TDR25	Digital product twin	0.6462	7
TDR30	Product carbon footprint monitoring	0.6458	8
TDR29	Interoperable components	0.6455	9
TDR17	User-friendly interface and control panels	0.6449	10
TDR16	Mobile app-based control and reporting	0.6419	11
TDR3	Integration of renewable energy	0.6417	12
TDR27	Data security	0.6382	13
TDR19	Remote technical support	0.6337	14

Table 7. *Cont.*

Code	Technical Design Requirements	Crisp Values	Rank
TDR22	Wireless sensor network	0.6336	15
TDR12	Real-time monitoring and control	0.6319	16
TDR28	Reliable alerts & notification system	0.6218	17
TDR20	Guaranteed parts & repair services	0.6177	18
TDR23	High-quality, low-power sensors	0.6173	19
TDR26	Compliance with standards & certifications	0.6129	20
TDR21	User manuals and documentation	0.6028	21
TDR15	Financial performance analysis and forecasting	0.5988	22
TDR18	E-learning and training modules	0.5931	23
TDR2	Energy-efficient LED lighting system	0.5797	24
TDR1	Energy-efficient HVAC system	0.5759	25
TDR7	Cost-effective automation system	0.5702	26
TDR4	Closed-loop water system	0.5630	27
TDR6	Organic waste management	0.5426	28
TDR5	Use of recyclable materials	0.5335	29
TDR10	Automated dosing, irrigation, and lighting	0.3022	30

4.3. Sensitivity and Robustness Analyses

4.3.1. Kendall's Coefficient of Concordance (Kendall's W)

To ensure the reliability of the collected data and measure the level of consensus among the four experts, Kendall's W) was calculated using IBM SPSS Statistics 25.0. The analysis yielded a Kendall's W value of 0.579 (χ^2(df = 16) = 37.078, p = 0.002). This statistically significant result demonstrates a moderate-to-strong agreement among the DMs [102]. Furthermore, to address the dispersion of expert responses, standard deviations and ranges were analyzed (Table 8). Despite the naturally diverging perspectives inherent in multidisciplinary panels, the experts reached a highly significant consensus regarding the fundamental TBL-oriented requirements of CEHA systems.

Table 8. Descriptive statistics and dispersion of expert evaluations for SNs.

SNs	N	Mean	Std. Deviation	Minimum	Maximum
ENS1	4	5.75	3.096	3	10
ENS2	4	8.00	4.899	2	12
ENS3	4	6.25	4.573	3	13
ENS4	4	8.00	2.708	4	10
ECS1	4	11.75	3.594	7	15
ECS2	4	16.25	1.500	14	17
ECS3	4	14.00	2.828	10	16
ECS4	4	15.25	0.957	14	16
ECS5	4	10.00	3.559	7	15
ECS6	4	9.75	2.754	7	13
EOS1	4	8.75	4.272	6	15
EOS2	4	7.25	5.188	1	12
EOS3	4	10.50	5.972	3	17
EOS4	4	10.25	3.594	5	13
SS1	4	3.00	2.708	1	7
SS2	4	4.00	3.162	1	8
SS3	4	4.25	3.403	1	9

The practical implications of employing FIT2 Gaussian fuzzy sets are clearly evident in the model's final outputs. While the decision-makers demonstrated a moderate-to-strong overall consensus (as validated by Kendall's W), they naturally prioritized specific needs (e.g., EOS3) due to their diverse professional backgrounds. The FIT2 Gaussian fuzzy approach improved the representation of this linguistic variance. Consequently, SS1, SS2, SS3, and ENS3 maintained their top-tier positions.

4.3.2. Leave-One-Out (LOO) Analysis

To directly assess the potential influence of the panel size on the stability of the results, an LOO sensitivity analysis was conducted on the expert evaluations. By systematically removing one DM at a time and re-aggregating the FUCOM weights, the structural robustness of the SN rankings was tested. As depicted in the radar chart (Figure 6), while minor local variations exist, the overall structure of the priorities remains highly stable. Critical SNs maintained their dominant positions near the center, while lower-priority criteria consistently remained at the outer boundary across all exclusion scenarios. To quantitatively validate this visual stability, Spearman's rank correlation coefficients (ρ) were calculated between the baseline model and each LOO scenario (Table 9). All correlation coefficients are exceptionally high ($\rho > 0.922$) and statistically significant ($p < 0.001$). This mathematical evidence confirms that the proposed framework is highly robust; the removal of any single DM's evaluations does not cause a statistically significant rank reversal in the stakeholder needs.

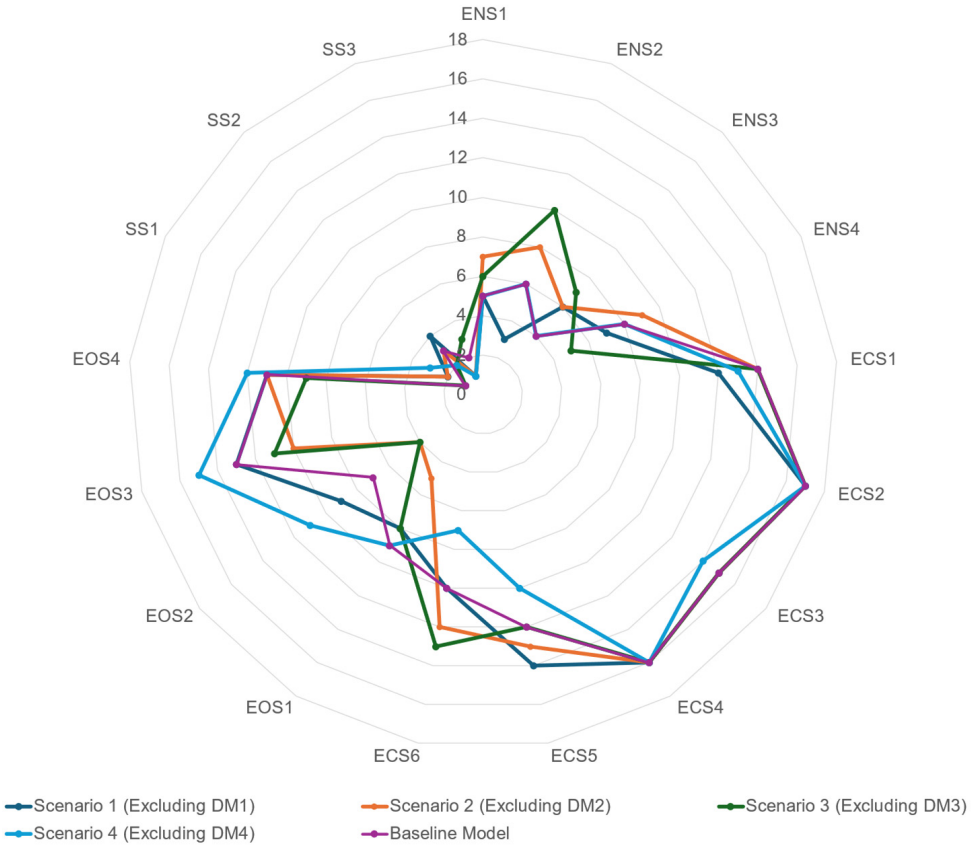


Figure 6. Radar chart illustrating the ranking across LOO scenarios and the baseline model.

Table 9. Spearman's rank correlation coefficients between the baseline model and LOO scenarios.

Sensitivity Scenario	Spearman's Coefficients (ρ)	p-Value
S1	0.963 **	<0.001
S2	0.934 **	<0.001
S3	0.922 **	<0.001
S4	0.949 **	<0.001

** Correlation is significant at the 0.01 level (2-tailed).

4.3.3. Weight Perturbation Analysis

A comprehensive sensitivity analysis was conducted to assess how changes in the weights assigned to the SNs would change the ranking of TDRs following the methodology proposed by Sumrit and Keeratibhubordee [103], with modified mathematical notation to ensure precise percentage adjustments. The selection of the SNs was grounded in the Pareto principle (the 80/20 rule). Since the top four criteria—SS1, SS3, SS2, and ENS3—account for a significant proportion of the weight distribution out of the 17 total SNs, a total of 24 scenarios were generated by systematically varying their weights by ±10%, ±20%, ±30%. To maintain the total sum of all weights equal to 1, the weights of the remaining SNs were proportionally adjusted whenever the weight of one SN was changed, as expressed in Equations (13) and (14).

$$w_i\ (1+\delta) + \sum_{k=1,k\neq i}^{m} \beta w_k = 1 \tag{13}$$

$$\beta = \frac{1 - w_i\ (1+\delta)}{1 - w_i} \tag{14}$$

where w_i is the initial weight of the criterion being varied, δ represents the variation coefficent (set at ±10%, ±20%, ±30%), β is the adjustment coefficient, and βw_k denote the adjusted weights of the remaining criteria ($k \neq i$), respectively.

The resulting rank dynamics are visualized in Figure 7. The analysis reveals that the model's output possesses a high degree of structural robustness. The top five technical requirements—scalable IoT infrastructure (TDR9), sensor maintenance and calibration (TDR14), AI-enabled decision support (TDR11), modular system design (TDR8), and data standardization (TDR24)—demonstrated remarkable stability, consistently occupying the highest ranks across all simulated scenarios. Although a minor rank exchange occurred between the top two priorities (TDR9 and TDR14), these requirements maintained their dominance as the leading pair in every scenario. Conversely, Automated dosing, irrigation, and lighting (TDR10) consistently ranked last across all variations. Collectively, these findings confirm that the proposed framework is resilient to variations in subjective weights.

4.3.4. Scenario Analysis of TDR Intercorrelations

Furthermore, to assess the impact of structural changes within the intercorrelation matrix (the HOQ roof), a zero-intercorrelation scenario was analyzed. As shown in Figure 8, eliminating internal TDR intercorrelations by assigning a no-correlation (N) value from Table 5 across the roof matrix fundamentally alters the HOQ's prioritization logic. For instance, without capturing technical intercorrelations, TDR9 drops sharply from rank 1 to 14, while low-priority parameters like TDR10 jump from rank 30 to 3. This comparative analysis explicitly demonstrates that the structure of the intercorrelation matrix is both mathematically and practically essential; real-world CEHA resilience relies as much on synergies between TDRs as on fulfilling SNs.

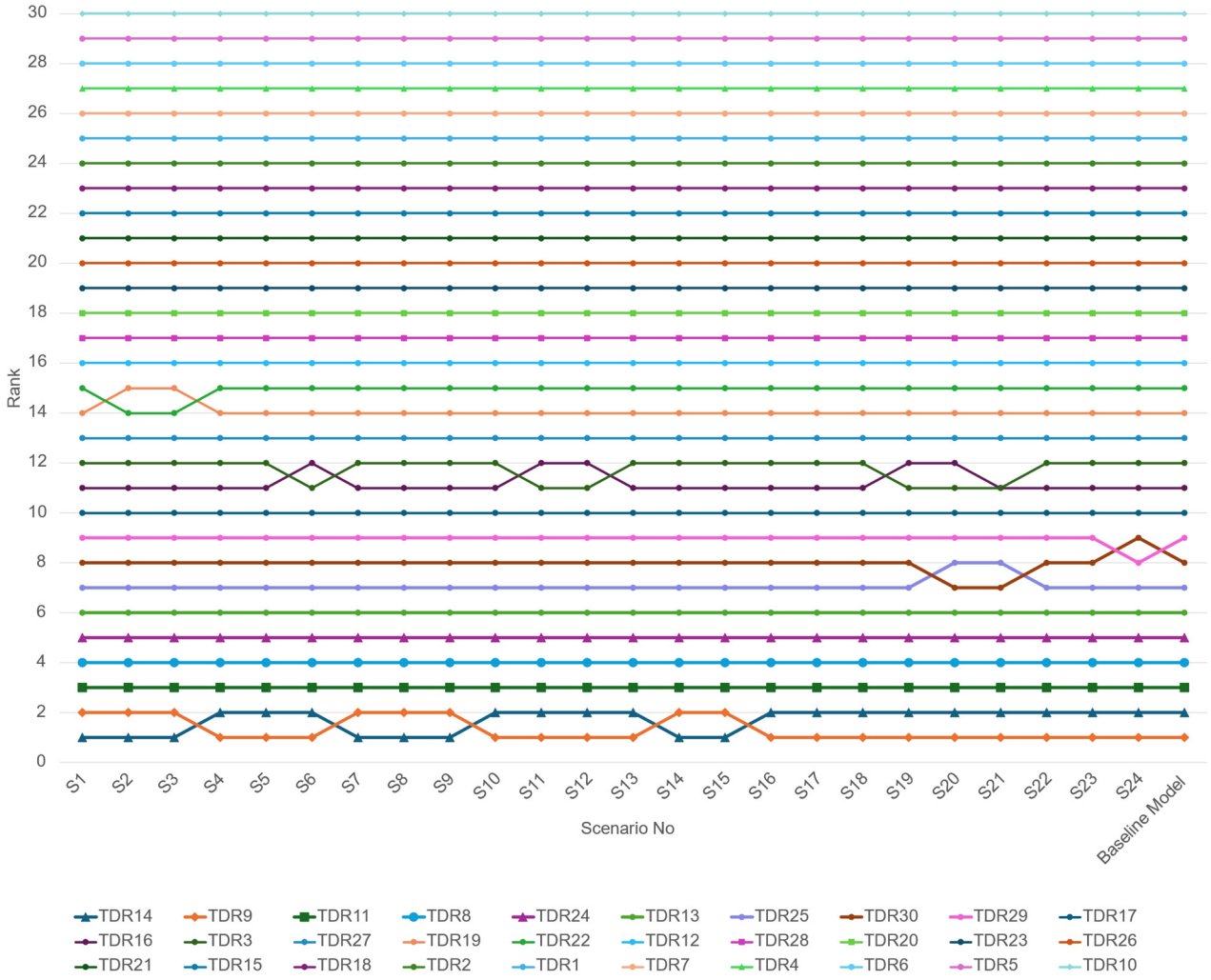


Figure 7. Comparison of TDR rankings across 24 sensitivity scenarios and the baseline model.

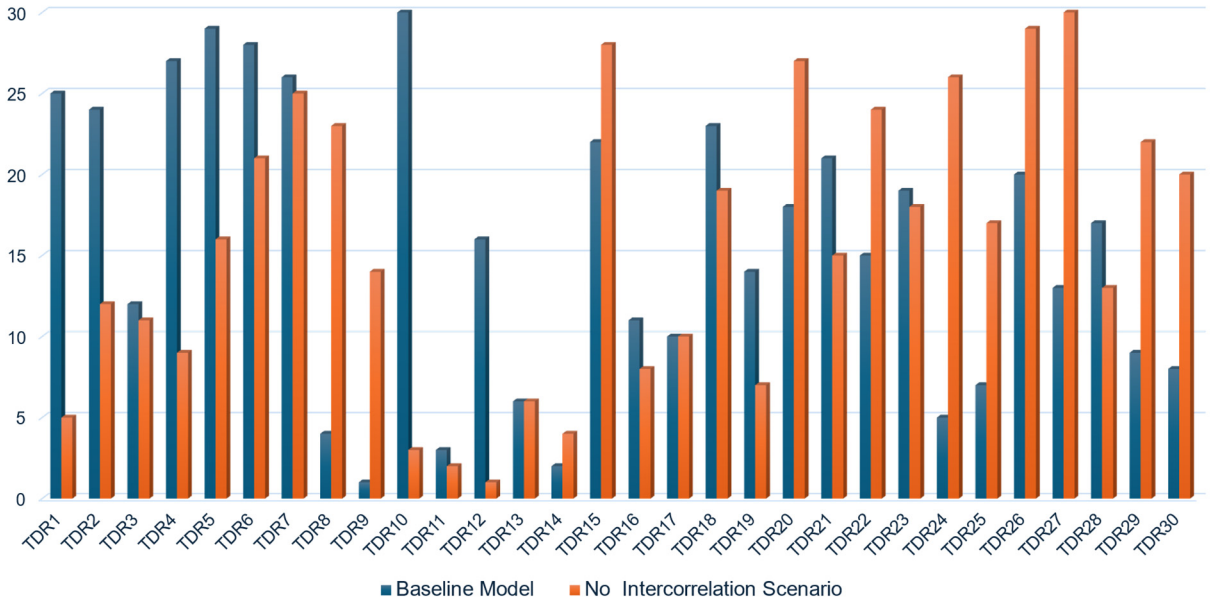


Figure 8. Comparison of TDR rankings between the baseline model and the no TDR intercorrelation scenario.

5. Discussion

5.1. Interpretation of the Findings

The FUCOM analysis shows that stakeholders prioritize environmental sustainability (ENS, 0.2629) and social sustainability (SS, 0.2626) as the top concerns. These findings align closely with Jonh and Artmann [52], which similarly concluded that the environmental dimension of urban agriculture holds the highest priority, followed closely by the social and economic dimensions. The dominance of the Environmental criteria can be attributed to the pressing need for efficient growing systems that leverage advanced technologies to meet sustainability goals. As Biancone et al. [21] argues that entrepreneurship in this field must leverage environmental awareness to facilitate localized food production and offer concrete solutions to production and sustainability pressures.

Another critical finding is the prominent priority weight assigned to social sustainability (0.2626), which is almost identical to that for environmental sustainability (0.2629). This alignment in criteria weights stems from the fact that SAFSCs are fundamentally social constructions. Consequently, stakeholders within these systems aim to build transparent and equitable networks, placing greater emphasis on fostering relationships, trust, and social capital rather than merely facilitating isolated product exchanges [28]. Furthermore, CEHA systems directly address these social needs by ensuring local food security. These indoor-grown foods are fresh, retain nutritional value, and are cultivated without pesticides, making them highly relatable to organic produce [42]. Beyond health benefits, the engagement of residents in urban CEHA systems fosters sustainable food behaviors [52] and creates valuable opportunities for new, independent entrepreneurs [42].

Although economic sustainability (ECS, 0.2551) ranks slightly lower, it remains a crucial baseline due to the significant capital investment required for CEHA systems [20,43]. This indicates that while environmental and social impacts are the primary value propositions, long-term economic performance and system reliability remain the foundational drivers of CEHA resilience [2]. Lastly, while ease of use and operational support (EOS, 0.2190) carry the lowest weight, it plays an essential enabling role. Although sustainability sets the strategic direction, operational ease is what ultimately translates technological potential into practical, widespread adoption [34].

At the sub-criteria level, high product quality (SS1, 0.0911) was identified as the top priority, closely followed by food safety and traceability (SS3, 0.0901) and consumer acceptance (SS2, 0.0812), and minimization of environmental impacts and sustainability (ENS3, 0.0690). This ranking highlights that a key value of IoT-based CEHA systems lies in their ability to reduce environmental impact by shortening supply chains, while delivering fresh, consistent, and traceable products [42]. The emphasis on Food Safety (SS3) aligns with the findings of Lezoche et al. [104], who demonstrated that IoT's primary social benefit is ensuring food safety and quality, thereby enhancing customer satisfaction. As Chen et al. [7] points out that this focus is especially important since maintaining high quality is a major challenge in AFSCs, influencing supply chain resilience and market competitiveness. Moreover, the high importance of food safety and traceability (SS3) underscores the core advantage of IoT-based CEHA systems in providing end-to-end visibility. Within a resilient AFSC, traceability act as a critical risk-management tool, ensuring that consistent, verifiable products reliably reach urban centers [42].

The QFD analysis translated the prioritized SNs into the five most critical TDRs: scalable IoT infrastructure (TDR9), sensor maintenance and calibration (TDR14), AI-enabled decision support (TDR11), modular system design (TDR8), and data standardization (TDR24). Their emphasis reflects a shift from conventional mechanization toward intelligent, data-driven, and interoperable CEHA systems.

Scalable IoT infrastructure (TDR9) and modular system design (TDR8) support incremental expansion, helping to stabilize system performance across different operational scales [44]. According to Adobor [105], scalability refers to system's ability to adjust its scale in response to changing conditions, while modularity allows for reconfiguration of functions and components relationships.

Beyond operational control, the Internet of Things (IoT) is recognized as a critical tool for supply chain management. By leveraging real-time data from IoT sensors, enterprises can more accurately monitor financial status, inventory levels, and operational risks [106]. In this context, Data Standardization (TDR24) is crucial because IoT devices often operate on diverse protocols, leading to heterogeneity [44], standardizing data ensures seamless information exchange among all stakeholders, enhancing coordination and efficiency across the supply chain [107].

At the same time, sensor maintenance and calibration (TDR14) and AI-enabled decision support (TDR11) are identified as crucial drivers for resource efficiency, enabling real-time adjustments to environmental conditions [20,34]. Specifically, integrating AI into CEHA systems enhances intelligent environmental control systems by enabling advanced data analytics and superior decision-making. By leveraging continuous sensor data, these AI algorithms can accurately predict plant responses to environmental fluctuations, thereby facilitating proactive adjustments that optimize resource utilization and crop quality [38].

Thus, the effective operation of CEHA systems depends heavily on advanced sensing technologies. Miranda et al. [92] emphasizes that smart and sustainable sensing is fundamental to Agri-Food 4.0, supporting the importance of proper sensor maintenance and calibration. Moreover, integrating AI with expanded IoT capabilities unlocks new possibilities for intelligent, adaptive, and content-rich applications. This integration aligns with the principles of Industry 5.0, which focus on human-centric, sustainable, and resilient systems [107].

Interpreting these rankings through Kano's model [108] provides valuable insights into system design priorities. Fundamental system components like an energy-efficient HVAC system (TDR1) and an energy-efficient LED lighting system (TDR2), a closed-loop water system (TDR4), and Automated dosing, irrigation, and lighting (TDR10) serve as essential prerequisites for market entry. Although they rank very low, this does not imply they are unimportant; rather, they represent "must-be" requirements that stakeholders expect as standard. As Zareba et al. [36] highlights, advancing to such intelligent systems is vital for integrating and optimizing resource flows in urban environments, including closed-loop water management, organic waste utilization, and the implementation of renewable energy sources. In contrast, the top-ranked TDRs act as dynamic drivers of stakeholder satisfaction. Scalable IoT infrastructure (TDR9) and sensor maintenance (TDR14) fall into the "one-dimensional" category, meaning that operational success and stakeholder satisfaction increase directly with their reliability [92]. AI-enabled decision support (TDR11), meanwhile, is classified as an "attractive" requirement.

Appendix D, Figure A3 presents a heatmap illustrating the relationships between SNs and the top 10 TDRs. As depicted, darker colors, indicating strong relationships, are heavily concentrated in the TDR11 column. AI-enabled decision support (TDR11) exhibits the strongest relationships with resource efficiency (ECS6), real-time environmental monitoring (ENS4), system usability (EOS2), and energy efficiency (ENS1), with scores of 0.485, 0.471, 0.468, and 0.454, respectively. This finding suggests that AI functions as a comprehensive optimizer for the entire CEHA system. Notably, the stakeholders' highest priority—high product quality (SS1)—is most strongly linked to AI-enabled decision support (TDR11) and sensor maintenance and calibration (TDR14). This underscores that achieving superior agricultural output and enhancing supply chain resilience depends on reliable sensor data combined with intelligent decision support.

Furthermore, Appendix D, Figure A4 displays a heatmap showing the correlations among the top 10 TDRs. The strongest correlations are found between the scalable IoT infrastructure (TDR9), modular system design (TDR8), and the interoperable components (TDR29). This indicates that scalable IoT infrastructure (TDR9) serves as a key enabler, essential for supporting continuous modular expansion and ensuring seamless communication among devices within the facility and the broader supply chain. Together, these findings emphasize that achieving true resilience in CEHA systems requires a shift from basic automation to data-driven, intelligent, and scalable sophisticated systems.

5.2. Managerial and Practical Implications

This study translates the complex SNs of CEHA systems into practical, actionable strategies. Our core findings indicate that stakeholders place the highest priority on delivering high product quality, ensuring strict food safety and traceability, and fostering strong consumer acceptance. As a result, engineering approaches must move beyond rigid, hardware-centric designs and instead emphasize scalable IoT infrastructures, modular system architectures, and AI-driven analytics to reliably meet these market expectations.

The practical utility of these findings becomes particularly evident during the planning of a mid-scale urban CEHA facility. As consortia of investors and agricultural engineers frequently face budget constraints, implementing all available Industry 4.0 technologies simultaneously is rarely feasible. Strategically, the framework proposed in this study is most useful during the conceptual design and early feasibility stages of such a project. Before committing to any significant capital expenditure (CAPEX), decision-makers can use our TDR rankings as a strategic investment roadmap. This allows them to first secure the essential "must-be" requirements of the system and subsequently allocate funds toward "one-dimensional" and "attractive" features. Based on the insights from our integrated model, we offer the following targeted recommendations.

For Agribusiness Entrepreneurs and Investors: Evaluating the system through the Kano model reveals that Scalable IoT Infrastructure (TDR9) and Sensor Maintenance (TDR14) are crucial "one-dimensional" features for consistent product quality, while AI-enabled decision support (TDR11) offers an "attractive" competitive edge. As [35] emphasizes, combining IoT with AI-enabled decision support is transforming vertical farming into a highly sustainable practice.

However, integrating these advanced technologies introduces critical economic and operational realities. The exceptionally high initial costs of comprehensive sensors and AI-driven management systems create significant entry barriers, particularly for small-scale operations or new urban farmers [38]. Moreover, the implementation risks are substantial; in commercial environments where downtime entails severe losses, rigorous maintenance and sensor calibration (TDR14) are imperative to reliable system performance [34].

Consequently, these technological investments must be justified through strict economic feasibility studies [38]. Given the high upfront capital required, founders often rely on venture capital. Yet, long-term viability hinges on embedding these digital capabilities into robust, TBL-oriented business models. Prioritizing marketability, environmental sustainability, and community engagement alongside advanced technology is essential to achieve both customer acceptance and long-term financial sustainability [30,109].

For System Designers and Engineers: The high initial and operating costs of vertical farming systems must be addressed by improving system design to enhance resource use efficiency (RUE) and by adopting circular business models [44]. From the design stage, engineers should prioritize interoperability and use modular components to enable smooth, scalable expansion. By using the proposed methodology in this study, designers can effectively translate stakeholder needs into evolving system requirements.

Regarding the physical architecture, applying circular-economy principles and sustainable resource management will become increasingly fundamental to plant factory design. System infrastructure should integrate renewable energy sources—such as solar, wind, or bioenergy obtained from plant waste—to reduce reliance on fossil fuels. Additionally, incorporating smart LED lighting and HVAC systems that precisely meet plant requirements can significantly reduce energy costs while ensuring plant growth. Future construction models must prioritize modularity and scalability to align with stakeholders' evolving needs and financial constraints, while rigorously assessing the environmental impact [38].

Finally, to effectively tackle global agricultural challenges, cutting-edge technologies must be accessible and highly efficient. Given the severe shortage of skilled workers in agriculture, technical teams should prioritize creating intuitive, user-friendly interfaces. The system's user interface should enable operators to remotely monitor and control environmental conditions via web access on both desktop and mobile devices [34]. To ensure smooth and successful operations, this accessible design must be supported by structured, long-term technical assistance, comprehensive training programs, and educational resources starting from the installation phase [46].

For Policymakers and Urban Planners: To promote the widespread adoption of CEHA systems and effectively integrate them into existing food supply chains, proactive urban planning and comprehensive public policies are essential [52]. Local governments must first legally acknowledge the hybrid nature of CEHA, which combines industry and agriculture. This recognition should lead to identifying suitable locations and adapting zoning regulations to support urban farming, such as repurposing underutilized urban facilities and warehouses into high-tech food production hubs [19,31,109].

Beyond spatial considerations, policymakers need to develop supportive financial frameworks. As CEHA systems scale up, increasing complexity and underscoring the need for ongoing research and development [44], public institutions should facilitate stable financing options through traditional lenders. Governments can also introduce targeted subsidies to improve yields and reduce GHG emissions, alongside promoting affordable electricity options in regions with subsidized energy [109].

Finally, raising public awareness and providing education are crucial to overcoming adoption challenges. Implementing training programs and enforcing clear, informative packaging and labeling will help emphasize the benefits of locally grown produce. Policymakers should highlight the role of urban plant factories in enhancing food security, fostering sustainability, and improving community well-being. By effectively leveraging these advantages, governments can build strong community support and ensure the long-term adoption of CEHA systems [20,46,109].

6. Conclusions

This study introduced a novel MCDM framework that combines FUCOM and QFD within a robust FIT2 Gaussian fuzzy environment. This approach is designed to systematically align strategic, TBL-oriented SNs with TDRs for CEHA system design. The model provides a clear pathway for translating stakeholder expectations into practical engineering specifications, positioning well-designed CEHA systems as a critical driver of agri-food supply chain resilience. By incorporating fuzzy logic, the methodology effectively manages the subjectivity and uncertainty inherent in multi-stakeholder decision-making within complex Agri-Food 4.0 contexts.

Our results demonstrate that integrating FIT2 Gaussian fuzzy with FUCOM and QFD, supported by group decision-making, provides a strong capability for handling fuzziness and ambiguity in sustainable system design. The findings reveal a clear strategic focus on environmental sustainability (ENS) and social sustainability (SS). Specifically,

high product quality (SS1), food safety and traceability (SS3), consumer acceptance (SS2), and minimization of environmental impacts and sustainability (ENS3) emerge as the primary drivers of CEHA adoption. Correspondingly, scalable IoT infrastructure (TDR9), sensor maintenance and calibration (TDR14), and AI-enabled decision support (TDR11) are identified as the most critical technological drivers for system resilience. These results suggest that while foundational hardware remains an essential "must-have," the future competitive edge and structural resilience of CEHA systems will rely heavily on their data-driven intelligence, modular design, and interoperability.

To comprehensively validate the reliability and robustness of these findings, a multi-stage sensitivity framework was executed. Expert consensus was first statistically confirmed via Kendall's W, while an LOO approach verified panel stability. Furthermore, the robustness of the proposed model was proven across 24 scenarios by varying the weights of the top four critical stakeholder needs. Finally, the TDR intercorrelation scenario analysis explicitly demonstrated the indispensable role of internal TDR synergies. Collectively, these rigorous analyses reinforce the structural and mathematical robustness of the proposed framework, confirming its real-world reliability.

Theoretically, this study demonstrates the effectiveness of FIT2 Gaussian fuzzy sets in modeling ambiguity within strategic CEHA system design. From a practical standpoint, the proposed model offers a structured approach that helps agribusiness stakeholders prioritize and allocate limited capital toward technologies that enhance long-term resilience and competitive advantage. Ultimately, directly incorporating subjective stakeholder judgments into the technical design process proves to be a valuable strategy for developing resilient, localized agri-food supply chains.

The primary limitation of this study is its reliance on the judgments of a specific expert panel, which may introduce regional or sectoral biases. To improve generalizability, future research should expand the panel to include a wider range of agronomists, policymakers, engineers, and investors. Methodologically, while the FIT2 Gaussian FUCOM approach offers high consistency, the QFD method is flexible and could be combined with other criterion weighting techniques such as SWARA, MEREC, or AHP for cross validation of the stakeholder panel. Additionally, comparative analyses using alternative fuzzy sets—like Spherical, Fermatean, and Pythagorean fuzzy sets—could further test the framework's mathematical robustness.

Finally, applying this framework to other advanced CEA contexts, such as aeroponics or aquaponics, would provide valuable insights into its adaptability across increasingly complex technologies. Ultimately, as Wang et al. [19] emphasizes, achieving truly sustainable, resilient, and scalable CEA systems requires a comprehensive transdisciplinary approach. Integrating advanced decision-support frameworks like the one proposed in this study with broader collaborative research will be essential for shaping the future of the agri-food industry.

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Abbreviations

The following abbreviations are used in this manuscript:

AFSCs	Agri-Food Supply Chains
CAFSCs	Conventional Agri-Food Supply Chains
SAFSCs	Short Agri-Food Supply Chains
CEA	Controlled-Environment Agriculture
CEHA	Controlled-Environment Hydroponic Agriculture
TBL	Triple Bottom Line
SNs	Stakeholder Needs
TDRs	Technical Design Requirements
FIT2	Finite Interval Type-2
QFD	Quality Function Deployment
FUCOM	Full Consistency Method
LOO	Leave-One-Out

Appendix A

Table A1. Detailed definitions and supporting literature for SNs.

Category	Code	SNs	Definition	References
Environmental sustainability (ENS)	ENS1	Energy efficiency	Efficient use of energy in lighting, HVAC, and pumping systems with low environmental footprint and cost.	[20,21,43,44]
	ENS2	Resource efficiency and waste reduction	Efficient use of water, pesticides, and nutrients with effective waste reduction and management.	[20,44]
	ENS3	Minimizing environmental impact and sustainability	Application of circular economy principles to minimize environmental impact and achieve sustainability goals.	[20,42]
	ENS4	Real-time monitoring and decision support systems	IoT-enabled monitoring for real-time data collection and informed decision-making.	[16,45]
Economic sustainability (ECS)	ECS1	Low initial investment cost	Reduced upfront investment requirements for CEHA systems.	[20,42–44,46]
	ECS2	Low operational and maintenance costs	Reduced operation and maintenance costs through automation and control systems.	[20,44,46]
	ECS3	Modularity and scalability	Expandable system design adaptable to changing production demands and supply chain volumes.	[20,44]
	ECS4	Reduced labor requirement	Decreased labor dependency through automated processes to ensure operational continuity.	[1,20,22]
	ECS5	Economic viability and profitability	Ensuring financial feasibility and profitability compared with traditional agriculture methods.	[34,43,44]
	ECS6	Operational efficiency and productivity	Improved precision, responsiveness, and resource optimization for higher productivity.	[1,16,20]

Table A1. *Cont.*

Category	Code	SNs	Definition	References
Ease of use and operational Support (EOS)	EOS1	Remote access and mobile control	Remote system monitoring and management via desktop and mobile devices.	[1,34,48]
	EOS2	System usability	User-friendly interface enabling efficient monitoring and control for non-technical operators.	[34,47]
	EOS3	Installation support and training	Availability of installation guidance and training for system operation.	[41,46]
	EOS4	Service support and warranty	Technical assistance and warranty ensuring operational continuity and resilience.	[46]
Social sustainability (SS)	SS1	High product quality (taste, shelf-life, freshness) (SS1)	Consistent production of high-quality crops with superior taste and shelf life.	[21,22,41–44]
	SS2	Consumer acceptance (SS2)	Increased consumer trust and acceptance through reliable performance and clear production information.	[41,42,44]
	SS3	Food safety and traceability (SS3)	Ensured food safety through traceability and visibility across all production stages.	[20,22,41]

Table A2. Detailed definitions and supporting literature for TDRs.

Code	TDRs	Definition	References
TDR1	Energy-efficient HVAC system	System to maintain stable temperature and micro-climate control to improve crop quality while reducing energy load.	[38]
TDR2	Energy-efficient LED lighting system	Minimize energy consumption while optimizing plant growth with LED lighting.	[34,38]
TDR3	Integration of renewable energy	Use renewable energy to lower operating costs and CO_2 emissions.	[1,38,42,48]
TDR4	Closed-loop water system	Recirculate nutrient solutions to minimize water use and prevent environmental release.	[42]
TDR5	Use of recyclable materials	Use environmentally friendly materials to reduce end-of-life impact.	[34]
TDR6	Organic waste management	Close resource loops by converting waste into usable compost, reducing overall waste.	[20]
TDR7	Cost-effective automation system	Affordable automation system for reliable environmental monitoring and control.	[34]
TDR8	Modular system design	Enable system expansion with modular components for easier upscaling.	[44]
TDR9	Scalable IoT infrastructure	Maintain stable performance across different operational scales and conditions.	[38]
TDR10	Automated dosing, irrigation, and lighting	Automate water, nutrient, and lighting management to reduce human error and ensure precision.	[20]
TDR11	AI-enabled decision support	Provide real-time insights to optimize resource usage, prevent crop diseases, and adapt strategies to environmental changes.	[1,35,38]
TDR12	Real-time monitoring and control	Continuously monitor the system and respond to environmental changes.	[34]
TDR13	Maintenance planning	Predict and schedule maintenance activities for sensors or actuators to prevent performance issues.	[43]
TDR14	Sensor maintenance and calibration	Ensure reliable performance through regular maintenance, inspection, and calibration of sensors.	[34]

Table A2. *Cont.*

Code	TDRs	Definition	References
TDR15	Financial performance analysis and forecasting	Analyze financial metrics to manage risks and enhance profitability.	[110]
TDR16	Mobile app-based control and reporting	Enable remote system monitoring, control, and reporting via mobile or web interfaces.	[34,48]
TDR17	User-friendly interface and control panels	Provide an intuitive interface for efficient interaction with the IoT system.	[34,38,111]
TDR18	E-learning and training modules	Offer user training to enable effective operation of the system.	[35]
TDR19	Remote technical support	Provide off-site diagnostics and assistance for system troubleshooting.	[47]
TDR20	Guaranteed parts & repair services	Ensure availability of replacement parts and repair services for operational continuity.	[47]
TDR21	User manuals and documentation	Provide detailed guides for system operation and troubleshooting.	[47]
TDR22	Wireless sensor network	Enable scalable and energy-efficient wireless connectivity for sensors.	[20]
TDR23	High-quality, low-power sensors	Deploy accurate, energy-efficient sensors for large-scale IoT monitoring of light, water, temperature, and other parameters.	[51]
TDR24	Data standardization	Ensure data aggregation and analysis enabling devices to seamlessly communicate and interact with each other.	[44]
TDR25	Digital product twin	Simulate and monitor farming processes to proactively predict failures and optimize operations.	[42,112]
TDR26	Compliance with standards & certifications	Meet industry standards to facilitate performance evaluation and market access.	[16]
TDR27	Data security	Protect data confidentiality, integrity, and authenticity from potential cyber threats.	[35,38]
TDR28	Reliable alerts & notification system	Generate automated alerts for deviations from optimal environmental conditions.	[16]
TDR29	Interoperable components	Enable various devices to communicate with each other seamlessly using data protocols and IoT communication standards.	[35]
TDR30	Product carbon footprint monitoring	Track greenhouse gas emissions to support sustainability reporting and lifecycle analysis.	[42]

Appendix B

Let there be two FIT2 Gaussian fuzzy numbers $\widetilde{A}$ and $\widetilde{B}$:

$$\widetilde{A} = \left(k_{A1}, m_A, k_{A2}; H_{A^U}, H_{A^L}\right)$$

$$\widetilde{B} = (k_{B1}, m_B, k_{B2}; H_{B^U}, H_{B^L})$$

The arithmetic operations division) between the FIT2 Gaussian fuzzy number $\widetilde{A}$ and the scalar e and the addition, subtraction, and multiplication operations between two given FIT2 Gaussian fuzzy numbers $\widetilde{A}$ and $\widetilde{B}$ are processed as follows.

Definition A1. *The scaling operation of an FIT2 Gaussian fuzzy number* $\widetilde{A}$*:*

$$e \otimes \widetilde{A} = (e \times k_{A1}, e \times m_A, e \times k_{A2}; H_{A^U}, H_{A^L}), \text{ where } \forall e > 0, e \in \mathbb{R} \quad \text{(A1)}$$

Definition A2. *The addition between* $\widetilde{A}$ *and* $\widetilde{B}$*:*

$$\widetilde{A} \oplus \widetilde{B} = \left(k_{A1} + k_{B1}, m_A + m_B, k_{A2} + k_{B2}; min(H_{A^U}, H_{B^U}), min(H_{A^L}, H_{B^L})\right) \tag{A2}$$

Definition A3. *The subtraction operation between* $\widetilde{A}$ *and* $\widetilde{B}$*:*

$$\widetilde{A} \ominus \widetilde{B} = \left(k_{A1} - k_{B2}, m_A - m_B, k_{A2} - k_{B1}; min(H_{A^U}, H_{B^U}), min(H_{A^L}, H_{B^L})\right) \tag{A3}$$

Definition A4. *The multiplication operation between* $\widetilde{A}$ *and* $\widetilde{B}$*:*

If $\widetilde{A} > 0$ *and* $\widetilde{B} > 0$:

$$\widetilde{A} \otimes \widetilde{B} = \left(k_{A1} \times k_{B1}, m_A \times m_B, k_{A2} \times k_{B2}; min(H_{A^U}, H_{B^U}), min(H_{A^L}, H_{B^L})\right) \tag{A4}$$

If $\widetilde{A} < 0$ *and* $\widetilde{B} > 0$:

$$\widetilde{A} \otimes \widetilde{B} \cong \left(k_{A1} \times k_{B2}, m_A \times m_B, k_{A2} \times k_{B1}; min(H_{A^U}, H_{B^U}), min(H_{A^L}, H_{B^L})\right) \tag{A5}$$

If $\widetilde{A} < 0$ *and* $\widetilde{B} < 0$:

$$\widetilde{A} \otimes \widetilde{B} \cong \left(k_{A2} \times k_{B2}, m_A \times m_B, k_{A1} \times k_{B1}; min(H_{A^U}, H_{B^U}), min(H_{A^L}, H_{B^L})\right) \tag{A6}$$

Definition A5. *The division operation between* $\widetilde{A}$ *and* $\widetilde{B}$*:*

$$\begin{array}{l}\widetilde{A} \oslash \widetilde{B} = \\ min\left(\frac{k_{A1}}{k_{B1}}, \frac{k_{A1}}{k_{B2}}, \frac{k_{A2}}{k_{B1}}, \frac{k_{A2}}{k_{B2}}\right), \frac{m_A}{m_B}, max(\frac{k_{A1}}{k_{B1}}, \frac{k_{A1}}{k_{B2}}, \frac{k_{A2}}{k_{B1}}, \frac{k_{A2}}{k_{B2}}); min(H_{A^U}, H_{B^U}), min(H_{A^L}, H_{B^L})\end{array} \tag{A7}$$

Definition A6. *Ranking FIT2 Gaussian fuzzy numbers by defuzzification/type reduction*

$$\delta_{\widetilde{A}}(x,y)^U = \left(\frac{k_{A1} + 4m_A + k_{A2}}{6}, \frac{H_1}{3}\right) \tag{A8}$$

$$\delta_{\widetilde{A}}(x,y)^L = \left(\frac{k_{A1} + 4m_A + k_{A2}}{6}, \frac{H_2}{3}\right) \tag{A9}$$

The final circumcenter:

$$\delta_{\widetilde{A}}(x,y) = \left(\delta_{\widetilde{A}}(x,y)^U + \delta_{\widetilde{A}}(x,y)^L\right)/2 \tag{A10}$$

The final ranking score $\rho\left(\widetilde{\mathrm{A}}\right)$ is derived using Equation (A13), where a higher value indicates a higher priority. If $\widetilde{\mu}\ A < 0$, multiply $\rho(\widetilde{\mathrm{A}})$ by -1.

$$\rho\left(\widetilde{A}\right)_x = \frac{\delta_{\widetilde{A}}(x)^U + \delta_{\widetilde{A}}(x)^L}{2} \tag{A11}$$

$$\rho\left(\widetilde{A}\right)_y = \frac{\delta_{\widetilde{A}}(y)^U + \delta_{\widetilde{A}}(y)^L}{2} \tag{A12}$$

$$\rho\left(\widetilde{A}\right) = \sqrt{\rho\left(\widetilde{A}\right)_x + \rho\left(\widetilde{A}\right)_y} \tag{A13}$$

Appendix C

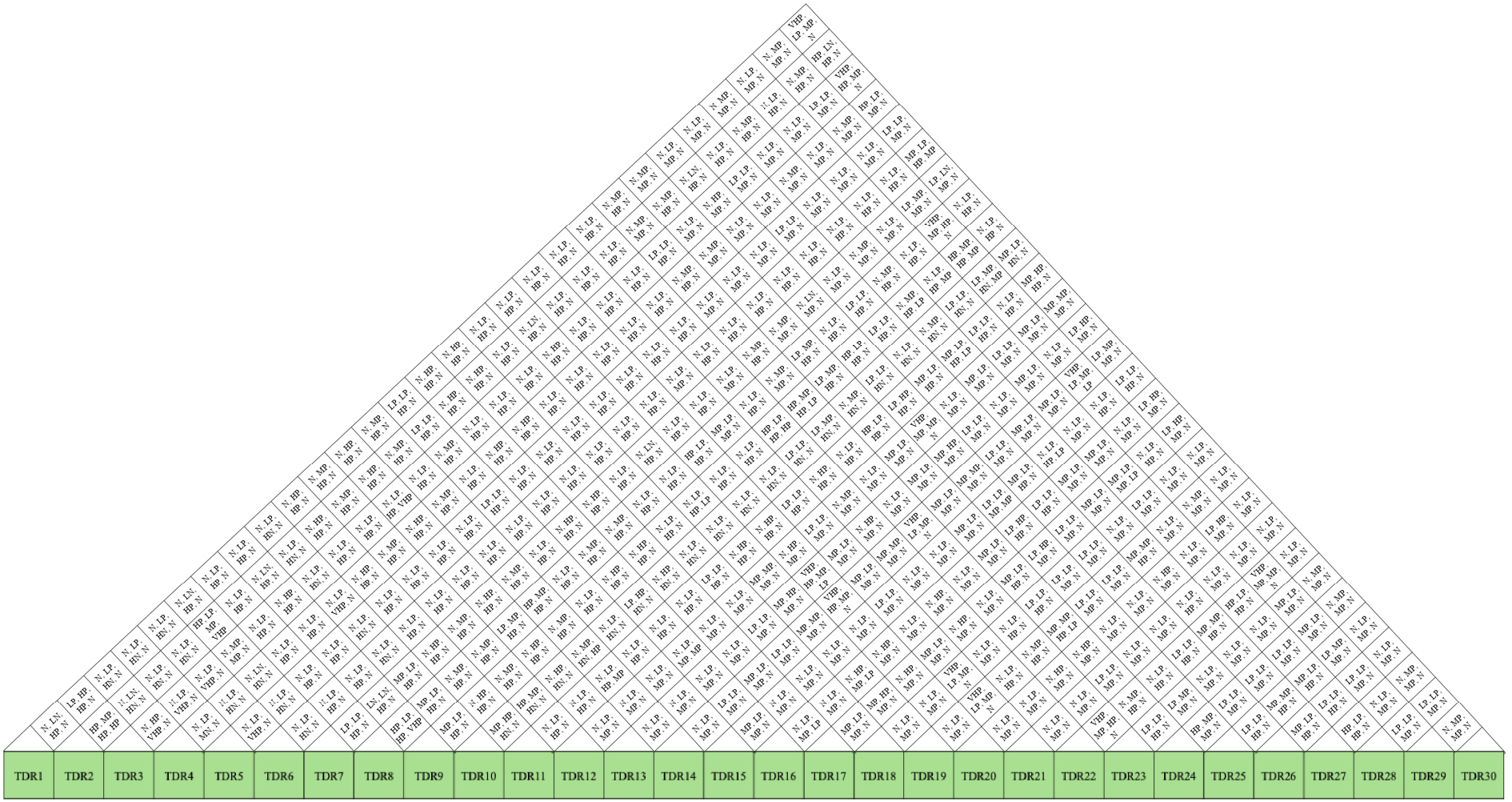


Figure A1. The roof (correlation matrix) of the HOQ.

HOQ		Weights	TECHNICAL DESIGN REQUIREMENTS (TDRs)																												
			TDR1	TDR2	TDR3	TDR4	TDR5	TDR6	TDR7	TDR8	TDR9	TDR 10	TDR 11	TDR 12	TDR 13	TDR 14	TDR 15	TDR 16	TDR 17	TDR 18	TDR 19	TDR 20	TDR 21	TDR 22	TDR 23	TDR 24	TDR 25	TDR 26	TDR 27	TDR 28	TDR 29	TDR 30
STAKEHOLDER NEEDS (SNs)	ENS1	0.068	VS, S, VS, VS	VS, S, VS, VS	VS, S, S, VS	W, S, W, VS	W, S, N, W	W, S, N, W	M, S, LW, S	M, S, N, LW	W, S, M, VS	S, S, S, W	S, S, M, S	W, S, S, M	W, S, S, S	W, S, S, M	S, M, N, W	W, M, N, S	W, M, LW, S	W, W, N, W	W, S, M, VS	W, S, W, LW	W, S, N, W	W, S, N, W	W, S, S, M	W, S, LW, M	W, S, S, VS	W, S, LW, W	W, S, N, M	W, S, S, W	W, S, N, M	W, S, S, VS
	ENS2	0.065	S, M, VS, W	S, M, VS, LW	S, S, S, W	W, S, VS, W	S, S, VS, S	S, S, VS, W	W, M, N, LW	W, M, W, W	W, M, M, W	S, M, S, VS	M, M, VS, S	W, M, VS , S	W, M, S, S	W, M, N, S	W, M, N, W	W, M, N, S	W, M, N, S	W, M, N, W	W, M, N, W	W, M, N, W	W, M, N, S	W, M, N, W	W, M, N, S	W, M, N, S	W, M, N, W	W, M, N, S	W, M, N, W	W, M, N, S	S, S, N, W
	ENS3	0.069	S, M, VS, W	S, M, VS, W	S, M, VS, W	S, M, VS, W	VS, S, VS, VS	S, S, VS, W	W, M, N, W	S, M, N, W	S, M, N, W	M, M, S, M	M, M, S, W	M, M, M, W	M, M, S, W	W, M, N, W	W, M, N, W	W, M, W, W	W, M, N, W	W, M, M, W	W, M, N, W	W, M, N, W	W, M, W, W	W, M, N, M	W, M, S, W	W, M, N, W	W, M, S, W	W, M, N, W	W, M, N, W	W, M, N, W	M, S, M, W
	ENS4	0.061	M, S, N, W	M, S, N, M	W, S, N, W	M, S, LW, M	W, S , N, W	W, S, N, W	W, S, N, M	W, S, N, W	W, S, N, M	S, S, N, W	S, S, S, S	VS, S, M, S	VS, S, N, S	S, S, N, S	M, S, S, W	VS, S, W, S	S, S, W, S	M, S, N, W	VS, S, N, M	M, S, N, W	VS, S, N, W	M, S, N, S	M, S, S, S	VS, S, S, M	S, S, N, W	S, S, N, S	VS, S, N, W	S, S, N, S	S, S, N, M
	ECS1	0.046	M, S, W, W	M, S, LW, M	W, S, N, W	W, S, LW, W	W, S , W, W	W, S, S, W	S, S, VS, W	M, S, S, W	M, S, S, W	W, S, S, W	W, S, W, W	W, S, W, W	M, S, N, W	M, S, N, W	S, S, N, W	M, S, N, W	W, S, N, W	W, S, N, W	S, S, W, W	S, S, N, W	S, S, N, W	M, S, N, W	M, S, M, W	W, S, N, W	W, S, W, W	LW, S, N, W	W, S, N, W	W, S, N, W	W, S, S, W
	ECS2	0.034	M, S, VS, W	M, S, VS, M	M, S, VS, W	W, S, VS, W	W, S, N, W	W, S, S, W	M, S, M, W	M, S, M, W	M, S, M, W	W, S, VS, W	M, S, VS, W	M, S, VS, W	VS, S, VS, W	S, S, VS, W	S, S, M, W	W, S, N, W	W, S, N, W	W, S, N, W	M, S, S, W	S, S, S, W	W, S, N, W	W, S, N, W	W, S, S, W	W, S, N, W	W, S, N, W	W, S, N, W	W, S, N, W	M, S, N, W	W, S, S, W
	ECS3	0.039	S, W, LW, W	W , W, N, M	W, S, W, W	W, W, M, W	W, W, N, W	W, W, N, W	M, W, N, W	S, W, VS, W	S, W, VS, W	S, W, N, W	W, W, N, W	W, W, S, W	M, W, N, W	W, W, N, W	W, M, N, W	W, M, W, W	W, M, N, W	W, M, N, W	W, S, N, W	W, W, N, W	M, W, N, W	M, W, N, W	W, W, N, W	W, W, S, W	W, W, N, W	W, W, N, W	W, W, N, W	W, S , S, W	W, W, N, W
	ECS4	0.035	M, W, N, LW	LW , W, N,	LW, W, M,	LW, S, M, LW	LW, W, N, W	LW, W, M, W	LW, W, N , W	LW, LW, W, M	LW, W, M , LW	VS, W, VS, W	VS, W, VS, S	VS, W, VS, M	VS, W, VS, S	M, W, VS, M	W, W, N, W	M, W, S, S	VS, W, S, S	VS, W, N, W	VS, W, VS, LW	M, W, N, W	VS, W, N, W	W, W, N, W	W, W, N, M	W, W, N, M	W, W, N, LW	W, W, N, W	M, W, N, W	W, W, N, M	W, W, M, LW
	ECS5	0.049	M, M, VS, W	M, M, VS, M	M, M, VS, W	W, M, VS, W	W, M, W, VS	W, W, VS, W	M, M, S, W	W, M, M, W	W, M, M, W	W, M, VS, M	W, M, VS, W	W, M, VS, W	W, M, S, W	W, M, S, W	VS, M, VS , W	W, M, N, W	M, M, N, W	M, M, N, W	S, M, N, W	VS, M, N, W	S, M, N, W	W, M, N, M	W, M, M, W	W, M, N, W	W, M, M, W	W, M, N, W	W, M, S, W	W, M, N, W	W, M, N, W
	ECS6	0.053	M, M, W, W	W, M, LW, M	W , M, VS, W	W, M, VS, W	W, M, N, W	W, M, VS, W	W, M, N, W	M, M, N, W	M, M, N, W	VS, M, VS, W	VS, M, VS, S	VS, M, VS, S	S, M, N, S	S, M, VS, S	M, M, N, W	S, M, N, S	S, M, N, W	S, M, N, S	M, M, N, W	S, M, VS, W	S, M, N, W	S, M, N, W	W, M, N, W	W, M, N, S	S, M, N, W	W, M, N, W	S, M, N, W	M, M, N, S	M, M, N, W
	EOS1	0.060	M, S, N, W	LW, S, N, M	LW, S, LW, W	LW, S, M, W	LW, S, N, W	LW, S, N, W	LW, S, N, W	M, S, N, W	M, S, VS, W	S, S, N, W	VS, S, N, M	VS, S, VS, M	S, S, N, M	M, S, N, M	LW, S, N, W	VS, S, VS, M	M, S, M, M	M, S, N, W	VS, S, VS , W	M, S, N, W	M, S, VS, S	M, S, N, W	M, S, N, W	M, S, N, W	M, S, N, W	S, S, N, M	W, S, S, W	W, S, S, M	M, S, N, W
	EOS2	0.062	M, S, S, W	W, S, LW, M	M, S, S, W	M, S, S, W	W, S, N, W	W, S, N, W	M, S, N, W	M, S, S, W	S, S, N, W	LW, S, VS, W	VS, S, VS, W	VS, S, VS, W	VS, S, S , W	M, S, M, W	W, S, N, W	S, S, VS, W	VS, S, S, W	VS, S, N, S	VS, S, VS , W	W, S, N, W	S, S, VS, S	W, S, N, W	M, S, N, W	W, S, N, W	M, S, S, W	W, S, N, W	M, S, S, W	W, S, M, W	M, S, N, W
	EOS3	0.048	M, S, W, W	W, S, N, M	M, S, N, W	W, S, N, W	LW, S, W, W	LW, S, N, W	W, S, W, W	LW, S, N, W	LW, S, N, W	M, S, N, W	M, S, N, W	W, S, N, W	S, S, N, W	W, S, N, W	W, S, N, W	S, S, N, W	S, S, VS, W	VS, S, VS, M	S, S, N, W	W, S, N, W	VS, S, VS , M	W, S, N, W	M, S, N, W	W, S, N, W	W, S, N, W	W, S, N, W	W, S, N, W	W, S, N, W	W, S, N, W
	EOS4	0.049	M, S, N, W	W, S, N, M	W, S, N, W	W, S, N, W	LW, S, N, W	LW, S, N, W	W, S, N, W	LW, S, VS, W	LW, S, VS , W	M, S, N, W	W, S, N, W	M, S, N, W	VS, S, VS , W	S, S, N, W	W, S, N, W	M, S, N, W	S, S, N, W	S, S, N, W	S, S, N, W	W, S, VS, S	W, S, N, W	S, S, N, W	W, S, N, W	M, S, N, W	W, S, N, W	W, S, N, W	M, S, N, W	W, S, S, W	W, S, N, W
	SS1	0.091	S, M, S, W	W, M, W, M	W, M, N, W	M, M, M, W	W, M, N, W	LW, M, N, W	M, M, N, M	W, M, N, W	M, M, N, W	S, M, VS, M	VS, M, VS , W	VS, M, VS, W	M, M, N, W	S, M, VS, W	W, M, N, W	M, M, N, W	S, M, N, W	S, M, N, W	M, M, N, W	W, M, N, W	M, M, N, W	W, M, N, W	S, M, N, W	W, M, N, W	M, M, N, W	W, M, N, W	M, M, VS, W	W, M, N, W	W, M, N, W
	SS2	0.081	W, S, W, W	M, S, N, M	W, S, W, W	W, S, N, W	M, S, M, W	W, S, N, W	LW, S, N, M	LW, S, N, W	LW, S, N, W	LW, S, N, M	S, S, N, W	VS, S, N, W	M, S, N, W	M, S, N, W	W, S, N, W	S, S, N, W	VS, S, N, W	S, S, N, W	S, S, N, W	S, S, N, W	W, S, N, W	W, S, N, M	W, S, N, W	W, S, N, W	M, S, N, W	M, S, VS, W	M, S, N, W	W, S, N, W	W, S, M, W
	SS3	0.090	M, W, LW, W	W, W, N, M	W, W, N, W	W, W, M, W	W, W, N, W	W, W, N, W	M, W, N, M	W, W, N, W	M, W, N, W	M, W, N, M	M, W, N, W	S, W, N, W	M, W, VS, W	M, W, VS, W	W, W, N, W	M, W, S, W	S, W, N, W	S, W, N, W	M, W, N, W	W, W, N, W	M, W, N, W	W, W, N, M	W, W, N, W	VS, W, N, W	W, W, M, W	M, W, N, W	W, W, VS, W	W, W, N, W	W, W, N, W
Relative Weights			(0.295, 0.480, 0.659; 1.0, 0.9)	(0.254, 0.422, 0.588; 1.0, 0.9)	(0.256, 0.433, 0.605; 1.0, 0.9)	(0.257, 0.442, 0.624; 1.0, 0.9)	(0.228, 0.394, 0.556; 1.0, 0.9)	(0.206, 0.367, 0.528; 1.0, 0.9)	(0.203, 0.357, 0.518; 1.0, 0.9)	(0.201, 0.363, 0.530; 1.0, 0.9)	(0.235, 0.401, 0.568; 1.0, 0.9)	(0.319, 0.494, 0.661; 1.0, 0.9)	(0.344, 0.525, 0.690; 1.0, 0.9)	(0.361, 0.552, 0.721; 1.0, 0.9)	(0.309, 0.482, 0.645; 1.0, 0.9)	(0.303, 0.482, 0.655; 1.0, 0.9)	(0.186, 0.341, 0.496; 1.0, 0.9)	(0.275, 0.445, 0.610; 1.0, 0.9)	(0.272, 0.440, 0.604; 1.0, 0.9)	(0.230, 0.389, 0.545; 1.0, 0.9)	(0.281, 0.452, 0.611; 1.0, 0.9)	(0.190, 0.346, 0.501; 1.0, 0.9)	(0.237, 0.396, 0.549; 1.0, 0.9)	(0.202, 0.363, 0.521; 1.0, 0.9)	(0.228, 0.391, 0.552; 1.0, 0.9)	(0.197, 0.358, 0.521; 1.0, 0.9)	(0.226, 0.392, 0.557; 1.0, 0.9)	(0.180, 0.339, 0.497; 1.0, 0.9)	(0.184, 0.334, 0.484; 1.0, 0.9)	(0.240, 0.410, 0.578; 1.0, 0.9)	(0.205, 0.365, 0.526; 1.0, 0.9)	(0.218, 0.384, 0.549; 1.0, 0.9)
Priority Weights			(0.851, 3.107, 6.048; 1.0, 0.9)	(0.748, 3.110, 6.218; 1.0, 0.9)	(1.449, 3.922, 7.309; 1.0, 0.9)	(0.633, 2.953, 5.846; 1.0, 0.9)	(0.468, 2.605, 5.351; 1.0, 0.9)	(0.509, 2.709, 5.506; 1.0, 0.9)	(0.728, 2.979, 6.064; 1.0, 0.9)	(1.612, 4.151, 7.772; 1.0, 0.9)	(1.816, 4.371, 7.676; 1.0, 0.9)	(−1.323, 0.850, 3.053; 1.0, 0.9)	(1.688, 4.219, 7.843; 1.0, 0.9)	(1.432, 3.760, 7.150; 1.0, 0.9)	(1.509, 3.949, 7.480; 1.0, 0.9)	(1.545, 4.189, 8.040; 1.0, 0.9)	(0.999, 3.286, 6.640; 1.0, 0.9)	(1.419, 3.856, 7.434; 1.0, 0.9)	(1.451, 3.899, 7.487; 1.0, 0.9)	(1.027, 3.246, 6.465; 1.0, 0.9)	(1.328, 3.768, 7.240; 1.0, 0.9)	(1.285, 3.604, 6.836; 1.0, 0.9)	(1.092, 3.369, 6.643; 1.0, 0.9)	(1.357, 3.795, 7.182; 1.0, 0.9)	(1.277, 3.559, 6.894; 1.0, 0.9)	(1.324, 3.940, 7.726; 1.0, 0.9)	(1.318, 3.899, 7.574; 1.0, 0.9)	(1.003, 3.422, 7.003; 1.0, 0.9)	(1.291, 3.798, 7.399; 1.0, 0.9)	(1.122, 3.564, 7.113; 1.0, 0.9)	(1.361, 3.878, 7.568; 1.0, 0.9)	(1.373, 3.884, 7.572; 1.0, 0.9)
Crisp Priority Weights			1.010	1.012	1.136	0.983	0.926	0.943	0.994	1.171	1.193	0.520	1.181	1.117	1.144	1.179	1.047	1.132	1.138	1.040	1.117	1.091	1.058	1.119	1.087	1.144	1.137	1.070	1.123	1.090	1.136	1.137
Normalized Priority Weights			(0.111, 0.711, 3.331; 1.0, 0.9)	(0.097, 0.711, 3.425; 1.0, 0.9)	(0.189, 0.897, 4.026; 1.0, 0.9)	(0.082, 0.676, 3.220; 1.0, 0.9)	(0.082, 0.676, 3.220; 1.0, 0.9)	(0.061, 0.596, 2.947; 1.0, 0.9)	(0.066, 0.620, 3.032; 1.0, 0.9)	(0.095, 0.681, 3.340; 1.0, 0.9)	(0.210, 0.950, 4.280; 1.0, 0.9)	(0.237, 1.000, 4.227; 1.0, 0.9)	(−0.728, 0.195, 1.681; 1.0, 0.9)	(0.220, 0.965, 4.319; 1.0, 0.9)	(0.187, 0.860, 3.938; 1.0, 0.9)	(0.197, 0.903, 4.120; 1.0, 0.9)	(0.201, 0.958, 4.428; 1.0, 0.9)	(0.130, 0.752, 3.657; 1.0, 0.9)	(0.185, 0.882, 4.094; 1.0, 0.9)	(0.189, 0.892, 4.124; 1.0, 0.9)	(0.173, 0.862, 3.987; 1.0, 0.9)	(0.167, 0.824, 3.765; 1.0, 0.9)	(0.142, 0.771, 3.659; 1.0, 0.9)	(0.177, 0.868, 3.956; 1.0, 0.9)	(0.166, 0.814, 3.797; 1.0, 0.9)	(0.173, 0.901, 4.255; 1.0, 0.9)	(0.172, 0.892, 4.172; 1.0, 0.9)	(0.131, 0.783, 3.857; 1.0, 0.9)	(0.168, 0.869, 4.075; 1.0, 0.9)	(0.146, 0.815, 3.918; 1.0, 0.9)	(0.177, 0.887, 4.168; 1.0, 0.9)	(0.179, 0.888, 4.170; 1.0, 0.9)
Crisp Values			0.576	0.580	0.642	0.563	0.533	0.543	0.570	0.661	0.668	0.302	0.666	0.632	0.647	0.668	0.599	0.642	0.645	0.593	0.634	0.618	0.603	0.634	0.617	0.651	0.646	0.613	0.638	0.622	0.645	0.646
Ranking			25	24	12	27	29	28	26	4	1	30	3	16	6	2	22	11	10	23	14	18	21	15	19	5	7	20	13	17	9	8

Figure A2. The central matrix of the HOQ.

Appendix D

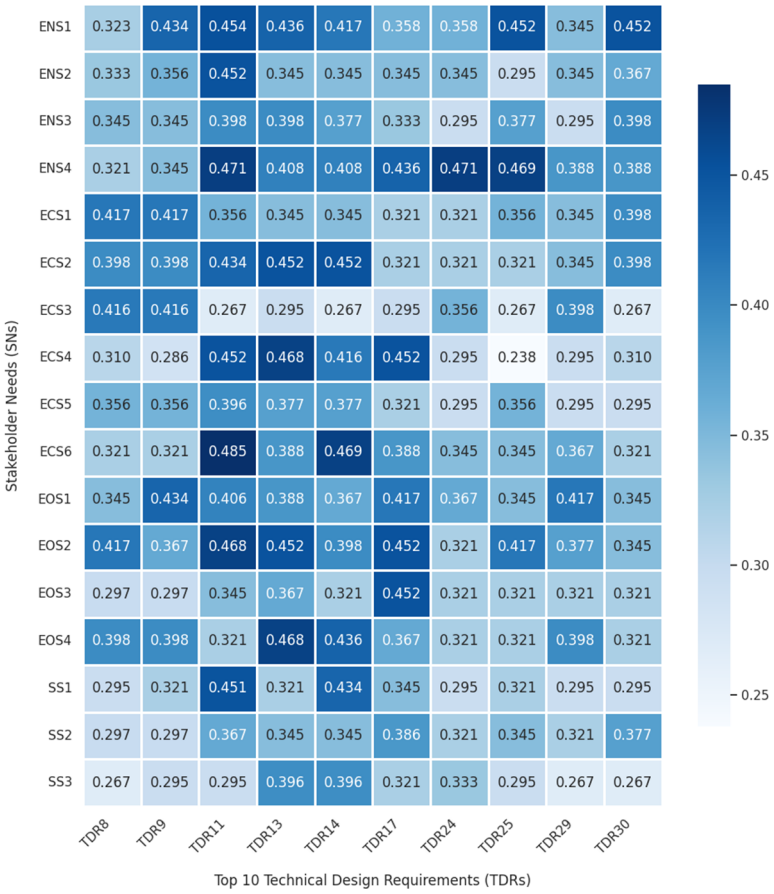


Figure A3. Heatmap of the relationship matrix between SNs and the top 10 TDRs.

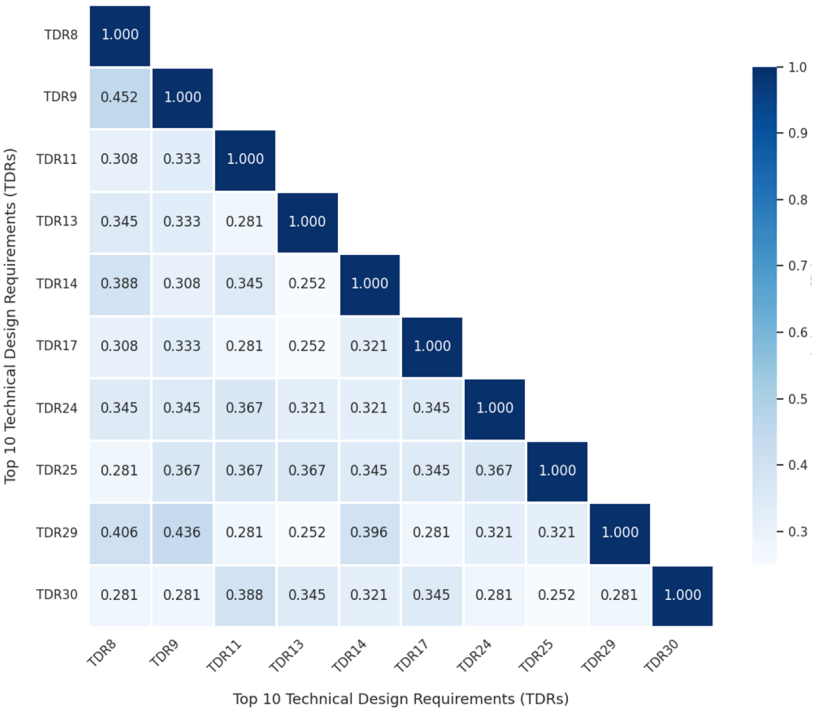


Figure A4. Heatmap of the intercorrelation matrix among the top 10 TDRs.

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