

Article

Enhancing Efficiency in Sustainable IoT Enterprises: Modeling Indicators Using Pythagorean Fuzzy and Interval Grey Approaches

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Abstract

“The Internet of Things” is a relatively new idea that refers to objects that can connect to the Internet and exchange data. The Internet of Things (IoT) enables novel interactions between objects and people by interconnecting billions of devices. While there are many IoT-related products, challenges pertaining to their effective implementation, particularly the lack of knowledge and confidence about security, must be addressed. To provide IoT-based enterprises with a platform for efficiency and sustainability, this study aims to identify the critical elements that influence the growth of a successful company integrated with an IoT system. This study proposes a decision support tool that evaluates the influential features of IoT using the Pythagorean Fuzzy and Interval Grey approaches within the Analytical Hierarchy Process (AHP). This study demonstrates that security, value, and connectivity are more critical than telepresence and intelligence indicators. When both strategies are used, market demand and information privacy become significant indicators. Applying the Pythagorean Fuzzy approach enables the identification of sensor networks, authorization, market demand, and data management in terms of importance. The application of the Interval Grey approach underscores the importance of data management, particularly in sensor networks. The indicators that were finally ranked are compared to obtain a good coefficient of agreement. These findings offer practical insights for promoting sustainability in enterprise operations by optimizing IoT infrastructure and decision-making processes.

Keywords: Internet of Things; enterprises; sustainable development; multi-criteria decision-making; Pythagorean Fuzzy Analytical Hierarchy Process; Interval Grey Analytical Hierarchy Process



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1. Introduction

The Internet of Things (IoT) is a field of engineering that aims to connect numerous small physical devices that can work together to accomplish a common objective. The widespread use of these small networked devices has increased the importance of IoT. These intelligent yet straightforward objects can detect each other wirelessly and communicate [1] and have sensing capabilities [2]. Smart devices are emerging on the market, supported by new paradigm-shifting technologies such as the Internet of Things and artificial intelligence (AI) [3]. IoT is a network of interconnected devices and services (computer hardware, machines, and physical items) that can sense their surroundings or themselves, run computer operations, and connect to the Internet. Smart items include cyber-physical

systems and Internet-based services. For instance, “smart” cars with cutting-edge embedded intelligence can connect to other cars, people, and the environment to provide creative data-driven services. These IoT-enriched products are “smartly connected” or “smart products”. Although “smart” is sometimes used to mean “intelligent”, “clever”, “nifty”, or “advanced”, the term “smart product” has considerably broader implications. Smart product creation requires new capabilities supported by cutting-edge tools, processes, and models, as these products are software-intensive, data-driven, and service-conscious.

Along with technological and financial advantages, the Internet of Things’ contribution to sustainability has grown in importance. IoT technologies are currently essential for achieving the sustainable development of enterprises, mainly because of their effects on responsible production, resource optimization, energy efficiency, and smart city infrastructure. Users access the Internet through various apps to conduct daily informational searches, browse specific websites, share documents, or communicate online, independent of time or space restrictions. Many states have recently explored opportunities for using IoT in various industries, including education, transportation, home appliances, healthcare, manufacturing, and smart cities. It is noteworthy that fourth industrial revolution involved the Internet of Things branching into the consumer and technology sectors. Strategic advantage realization is tied directly to the expected business transformation driven by digitization and the Internet of Things. IoT, a new informational engine, is projected to propel the communication technology market in the coming years [3]. Using IoT-enhanced items can be significant for understanding how, why, and when customers buy and use certain products. As a result, there is potential for interactive customer communication. IoT provides platforms that allow computing devices to accept, store, and transfer data across the Internet.

The twenty-first century has seen rapid advancements in industry, technology, and social convention. The plurality of industries has shifted toward automation, and human participation has decreased, resulting in an industrial revolution known as Industry 4.0. IoT and wireless sensor networks (WSNs) are crucial to Industry 4.0, often called the fourth industrial revolution (IR 4.0) [4,5]. Smart technologies are essential for long-term economic success. Without human interaction, they transform buildings into autonomous, self-regulating systems, including homes, workplaces, factories, and even entire cities [6]. Enabling commercial operations both within factories and outside markets is the IoT’s ultimate purpose. Companies face obstacles when implementing novel ideas. Many scholarly publications have examined security challenges, including data on tracked actions from hardware, software, and intelligent gadgets. Industry 4.0 IoT connectivity allows devices to communicate and interact with each other automatically. The hazards of exposure to sensitive information, such as personal information in the human resources department, financial data, and documents in the R&D office, are increased by this function. IoT combines the Internet’s strength with the ability of businesses to operate infrastructure, machinery, and factories [7]. IoT devices can be managed by end users using their smartphones or voice commands. The Internet of Things enables control over objects (such as computers, networks, laptops, etc.) to create products or services, ensuring the smart enterprise’s delivery [8]. IoT is essential for connecting the digital and physical worlds; however, several obstacles need to be overcome in the future.

Enterprises face challenges in selecting and prioritizing the most influential factors for IoT implementation due to data uncertainty, subjective preferences, and a lack of structured evaluation frameworks. Previous studies focused on isolated applications of fuzzy or grey-based methods in areas such as supply chains, healthcare, or smart cities [9,10], but relatively few have developed integrated decision models specifically addressing sustainability in IoT enterprise settings. To fully realize these benefits, enterprises must

systematically evaluate and prioritize IoT factors, ensuring that implementation efforts align with operational and strategic goals [11]. Effectiveness and transparency in procedures are examples of invisible improvement, whereas adjustable productions and various completed commodities are examples of visible improvement [12]. Because automatic equipment can communicate with devices without waiting for human input or commands, they can drastically minimize the waiting times of the production process and increase productivity [13]. Self-starting appliances can improve operation cycles based on the data gathered in “big data” pools, reduce setup time between units, and increase machine utilization [14]. This enables operators and management to make quick decisions to meet client demands. Additionally, implementing IoT in manufacturing would reduce gaps between operators, departments, and workshops.

Moreover, this strategy helps businesses conserve energy and address environmental challenges, as automated equipment typically uses less energy. Because their processes are transparent and efficient, manufacturing companies can create more customized products at a lower cost. This enhancement enables companies to expand their client base across multiple industries. These effects directly support key sustainability pillars, such as energy efficiency, climate action, and circular economy models. Thus, evaluating the effectiveness of IoT adoption is not only a matter of technological or business interest but also a pathway to achieving broader sustainability goals.

To evaluate IoT performance indicators in corporate contexts, this work contributes to the academic body of knowledge by presenting a novel hybrid approach that combines the Pythagorean Fuzzy Analytical Hierarchy Process (PFAHP) and the Interval Grey Analytical Hierarchy Process (IGAHP). The method enhances decision-making precision in situations involving imprecision and ambiguity, which are common in strategic planning associated with IoT. Our model provides a multi-criterion, generic framework that promotes operational efficiency and strategy alignment across various industries, in contrast to earlier research, which primarily focused on discrete industry use cases.

Hybrid fuzzy–grey MCDM methods have been applied in various fields, including logistics, energy planning, and smart city systems; however, their application in enterprise-level IoT implementation remains limited. Previous studies have primarily focused on specific use cases or employed single-method approaches that do not fully capture the multidimensional uncertainty inherent in IoT adoption processes. This study aims to bridge this gap by introducing a hybrid framework that combines the PFAHP and IGAHP methods, which is adapted to the challenges of assessing IoT success factors in business contexts. The PFAHP method takes into account ambiguity and hesitation in expert judgment, while the IGAHP compensates for incomplete or imprecise data. The results of the decision-making process are more dependable and applicable thanks to this mix of techniques. This study offers methodological advancements as well as practical significance for strategic planning in data-driven, sustainable companies by integrating important indicators, including information privacy, sensor networks, market demand, and data governance.

The article is structured as follows: Section 2 presents the theoretical background and factors influencing IoT. Section 3 defines indicators and provides a hierarchical structure, as well as the methodology for PFAHP and IGAHP. Section 4 presents the results and discusses the ranking of indicators, and provides recommended key tasks for enhancing efficiency in sustainable IoT enterprises. This study is concluded in Section 5, which also suggests some areas for further research.

2. Theoretical Background

When measuring the effectiveness of IoT adoption in enterprises, it is important to first understand the fundamental aspects that define this process. This section provides the theoretical background by listing and describing the essential criteria that affect the implementation and sustainability of IoT technologies in business environments. These aspects serve as the basis for developing the hierarchical structure used in the multi-criteria decision-making methodology.

2.1. Factors Influencing IoT

IoT devices have been widely used in different settings and circumstances [15]. According to [16], IoT involves the integration of numerous heterogeneous networks, and connection and security challenges between various networks need to be addressed. IoT devices have lower computing, storage, and network capacities compared with smartphones, tablets, and desktops, making them more susceptible to external attacks [17]. All IoT gadgets can connect to the Internet, record user habits and personal information, and then offer recommendations to consumers. Moreover, end users can control these IoT products via their voices or smartphones. This research evaluated the IoT framework for small and medium enterprises. This study's literature review identifies five key influencing criteria: connectivity, telepresence, intelligence, security, and value (Table 1).

Table 1. Factors influencing IoT adoption in enterprises.

Main Criteria	Description	Literature Review
Connectivity	The ability of IoT systems to exchange and transmit various forms of data from computer devices is known as compatibility.	[18–26].
Security	Safeguarding IoT systems and data through access control, encryption, authentication, and privacy mechanisms.	[18,20,21,24,25,27–33].
Intelligence	The ability of IoT systems to autonomously collect, process, and respond to data through embedded intelligence or AI-based decision-making.	[18,20,24–26,34–36].
Telepresence	IoT-enabled remote presence and interaction that allows real-time monitoring and coordination across distant locations.	[18,20,24,26,37–40].
Value	A user's subjective assessment of the deployment of IoT technology.	[18,20,23,24,41–45].

2.1.1. Connectivity

Connectivity establishes ongoing communication between IoT devices and other devices using IoT technology in companies. According to ref. [19], the backend systems supporting IoT devices are essential for delivering communication to successful applications and maintaining their smooth operation. The integrated operating interface for every user with any IoT device is the same; based on the definition of standards in IoT connectivity, finding a comparable network capacity for users residing in different countries is quite challenging for businesses. According to the findings of [20] on connectivity, businesses can use IoT technology to maintain communication between IoT facilities and items. According to [46], the IoT's connectivity comprises standardization, compatibility, and sensor

networks. Sensor networks are the first layer to transform information once IoT devices receive data from users. These data should be adaptable and compatible across various IoT appliances; hence, connectivity across various information types and IoT facilities is also a key factor for IoT connectivity [22]. One of the key strengths of IoT systems is their capacity to link numerous devices with varying properties. Due to this connectivity, we can share information to provide services, opening up new markets for apps and connected objects [25].

Sensor networks, standardization, and compatibility are key factors that determine connectivity. Compatibility is a capability in IoT systems that allows multiple data types to be transmitted and analyzed between IoT devices and objects [46]. Every user's operating interface for any IoT device must be integrated as part of the standardization process [23]. The sensor network is the first layer to transform data; therefore, it should be compatible and interchangeable between various IoT devices and objects [26].

2.1.2. Security

Security refers to the level of protection businesses and their staff offer when sharing information across departments [20]. Data management, authorization, and privacy are all included in this protection. The relevant information might be linked to particular guidelines and limitations that restrict the application of IoT technology. Although the Internet of Things has transformed the way people use technology, there are still significant risks associated with these innovations. According to [28], the relevant legislation must include the right to information, provisions banning or restricting the use of IoT mechanisms, rules for IT security legislation, regulations promoting the use of IoT mechanisms, and the establishment of a task force to research the IoT's legal challenges.

In addition, IoT devices should have four data protection features: client privacy, data authentication, access control, and resilience to attacks. Taking proactive steps to guard against malicious program attacks is part of the resilience against attacks. Data authentication refers to the process of organizing stored data by department and assigning it to appropriate users; resilience efforts aim to prevent harmful program attacks. Access control involves verifying the identity of employees or managers before granting them access to the database and requiring supervisor approval before transmitting data to the following level. Customer privacy requires businesses to always prioritize their customers' online activity history. Although [46] found that customers were highly compelled to adopt IoT technologies or products, the security and privacy concerns between IoT and traditional wireless networks are quite different [27]. The safety of IoT messages within intelligent elements symbolizes the level of confidence in businesses when a connection between smart devices occurs. IoT devices gather information on our usage patterns and operating history. Maintaining our personal and professional privacy is often compromised due to this [29]. According to the International Cooperation Report, 2017, just over half of the 3100 businesses surveyed globally had adopted IoT, and 84% had experienced a security breach in 2016. While 85% of the more than 5000 businesses surveyed globally have deployed or plan to deploy IoT devices, only 10% are confident in their ability to protect those devices from hackers. Because security concerns encompass hardware, software, and networks, configuring and updating devices to safeguard them against malicious software will be difficult. IoT also raises significant transparency and privacy concerns. The primary factors for security include data management, authorization, and information privacy. A mechanical feature called data management restricts who can access, use, and manage documents [26]. Customers have a strong desire for information privacy when adopting IoT technologies or products [47]. Authorization is a feature that enables authorized users to access specific data in databases whenever needed [32].

2.1.3. Intelligence

IoT intelligence is described in [20] as the level of comprehension that operators require when interacting with IoT devices to obtain information from them or provide instructions to execute tasks. IoT gadgets differ from traditional Internet-connected devices in that they have an intelligence element. IoT devices can also intelligently process input data to provide instructions that enable them to perform specific tasks. According to [48], to set the IoT apart from traditional Internet usage, IoT devices must incorporate the attribute of “intelligence” into their constituent parts. Whether IoT devices have a functional orientation or act as personal assistants for enterprises, as mentioned in [34], is another key consideration for businesses when developing smart IoT solutions. Smart devices’ features will be equipped with knowledge, comprehension, application, and analysis if they are functionally oriented, making them better at problem-solving and more effective, dependable, and reliable systems for business users. Businesses worldwide have incorporated this concept into various business models, developed smart IoT products, and brought them to market. Researchers are still developing new strategies and methods for reducing human effort in the IoT and AI fields [49]. Artificial intelligence, which enables IoT apps to connect with humans, is the defining property of smart IoT applications [35]. Cloud computing is another essential technology that enables the achievement of important intelligence functions. It provides an invisible area for end users to store, manage, and continuously interact with the enormous amount of data, linking them with other IoT components to assist businesses in making better decisions [26]. With this capability, IoT facilities will be able to collect real-time data, display it on a screen, evaluate it, and then make decisions by combining data from multiple sensors, thereby extending the lifespan of the network [36].

2.1.4. Telepresence

Wireless technology links between various Internet-connected gadgets can enable meetings without physical participation. Trustworthy IoT products leave customers with a favorable impression of the service. IoT is a unique paradigm that uses wireless technology to connect the pervasive presence of numerous things to the Internet to accomplish desired goals. Consumers will have a favorable experience and perception of an IoT product if it offers dependable telepresence capability. IoT requires a comprehensive telepresence feature and networking framework [37]. Telepresence is a service category offered by IoT devices that enables staff members and managers at all levels to simultaneously coordinate via a remote office from around the globe, view the latest events, and direct or conduct judgments using IoT facilities.

IoT uses context awareness to localize and customize information and integrates acquired data into the physical world for real-time synchronization and monitoring. The telepresence function is also considered a form of synchronization. Internal networks store all of a company’s information in the cloud. Employees working in different workplaces can see the same data while discussing the same topic. Monitoring and controlling are two additional aspects of telepresence. The primary purpose of both is to record the performance of IoT operators or equipment in real-time from many locations at any given moment [38]. Enterprises could contract performances on each device’s production and grasp their adjustments from analytical data to adapt product lines if these two capabilities are synchronized. More customization options and the highest production level at lower costs are also anticipated. Company information is also stored in the cloud by internal networks thanks to synchronization [23]. Monitoring is a feature that oversees the operation of IoT devices or operators in real time from various locations [39]. Controlling IoT equipment or operators from multiple locations in real-time is a means of providing guidance.

2.1.5. Value

When businesses attempt to create IoT business models, benefits significantly impact their attitudes and behavioral intentions [46], and the offer's value is a crucial building block in this process [41]. The IoT value refers to users' opinions on the market, convenience, and performance when adopting IoT technology. The IoT is heavily influenced by real market needs, particularly in the ICT sector. Additionally, credible information ensuring market success must be provided to investors and businesses to promote IoT market involvement. Companies need critical success criteria to accomplish their missions and goals in the short term [42]. Businesses need their supply chains to be more adaptable and to fulfill orders promptly for every transaction to reduce their lead times and operational costs as much as possible. This type of convenience might evolve into products and services that enable staff members to manage their work effectively and act quickly. IoT should be viewed as the foundation for a new business model that monetizes data from an intelligent ecosystem rather than just as a way for manufacturing enterprises to cut costs [43]. The IoT's convenience can be used to alter manufacturing procedures, create new products, or aid managers in making better marketing choices [26]. After receiving data from IoT devices, enterprises can learn about various business concerns, such as client preference changes or employee performance. As a result, businesses may alter their strategy for conducting business and offer guidance to employees whose performance at work is subpar. The primary factors for value include market demand, convenience, and performance. People can complete tasks more quickly using IoT environments and workflows [41]. In this context, the adoption of IoT technologies can significantly contribute to achieving sustainable development by supporting responsible consumption, resource efficiency, and data-driven environmental decision-making in enterprises [45].

However, the IoT enterprise's decision-making process must address data inconsistency and uncertainty. The opportunity to address numerous significant issues that impact business performance is made possible by the interconnected IoT devices. The primary hierarchical levels of enterprises are provided in Table 2.

Table 2. Main hierarchical levels of enterprises [50].

Hierarchical Levels	Description of Hierarchical Levels
Strategic level	The top managers perform some activities and make judgments to accomplish the strategic enterprise goals. Strategic policies have an impact on the performance and success of businesses. There are unpredictable situations in the environment at the strategic level.
Tactical level	The middle managers create a plan to accomplish the goals and targets set at the strategic level. Decisions at the tactical level would be clearer than those at the strategic level since tactical-level decisions are more specific to the individual business rather than being adopted generically. Decision-making processes should be quicker and more tailored.
Operational level	Decisions made at the operational level affect day-to-day activities that help the strategic and tactical levels realize their vision and strategies. The junior managers in the organization can adopt operational levels.

Today's technology is advancing so quickly that there is a growing need for the Internet. Considering today's technology, IoT, introduced with Industry 4.0, is crucial for businesses. Every business must switch to IoT to stay competitive; however, businesses face expensive and time-consuming challenges during the transformation process.

The means of disseminating product information have increased since the advancement of Internet technology and the emergence of social networks. Nowadays, a consumer's information perception is composed of both the product quality information they can acquire from real-world contacts and the product cognition information they can obtain via virtual networks. However, by improving the diffusion of information on the Internet, businesses can modify how their customer base perceives their products, control market knowledge, and increase corporate revenue. Decision-making using a business model with hierarchical levels is illustrated in Figure 1.

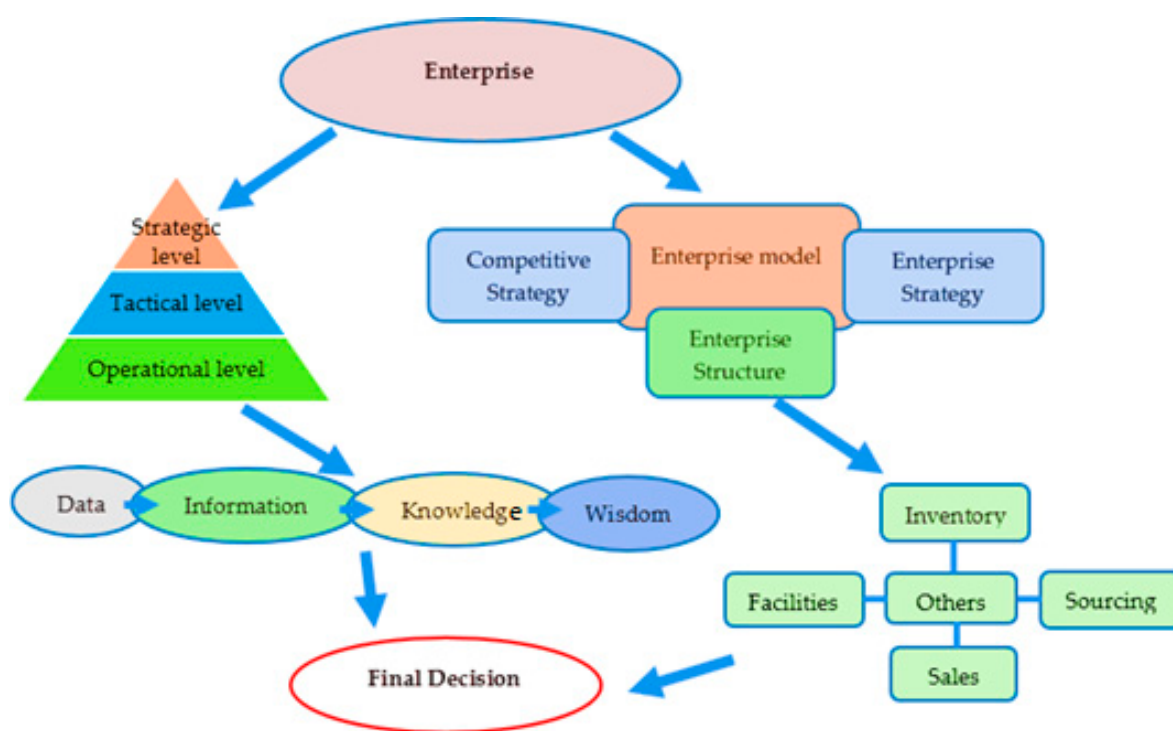


Figure 1. Hierarchical levels and enterprise models for reaching a decision.

The Internet of Things is defined as a network of networked items that do not require human intervention. Anyone can access the necessary content from anywhere to complete medical, business, or personnel duties. Enterprise IoT applications enable companies to significantly benefit from integrating IoT technologies with their existing applications. Supply chains, connected cars, retail, agriculture, and other industries are examples of enterprise IoT applications. IoT reference layers imply that definitions and reference layers can be used to construct IoT designs. Inventory, facilities, sales, sourcing, and other applications are all part of the enterprise structure. IoT structural details are shown in Figure 2.

A comprehensive framework for locating, classifying, and evaluating performance metrics for IoT systems in businesses is illustrated in Figure 2. Because most IoT scenarios involve ambiguity and incomplete information, MCDM techniques such as PFAHP and IGAHP can be applied to indicators to facilitate decision-making in these situations.

Given the intricacy and unpredictability of implementing IoT solutions in contemporary businesses, a methodological approach that enables a methodical assessment of pertinent elements must be used. In the next chapter, the research framework will be explained in detail, including the application of the multi-criteria methods PFAHP and IGAHP, the structure of the hierarchical model, as well as the process of collecting and analyzing expert data

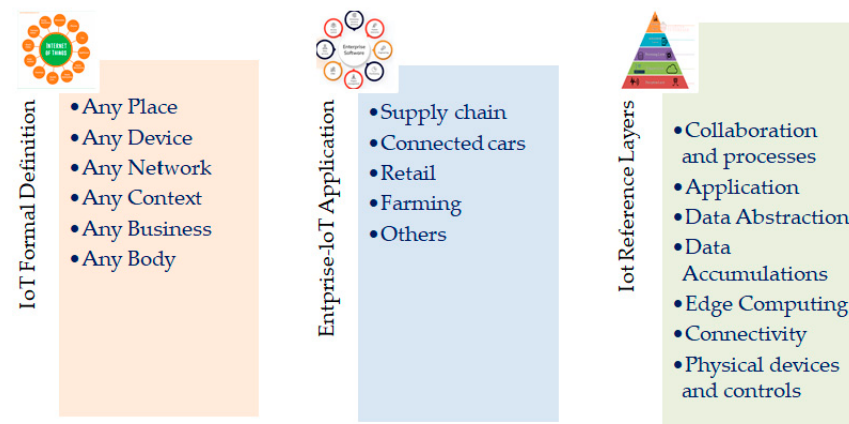


Figure 2. IoT definitions, applications, and reference models.

3. Materials and Methods

3.1. Problem Formulation

The methodological framework for this study was designed to systematically evaluate significant indicators that affect the adoption of IoT in sustainable initiatives, as shown in Figure 3.

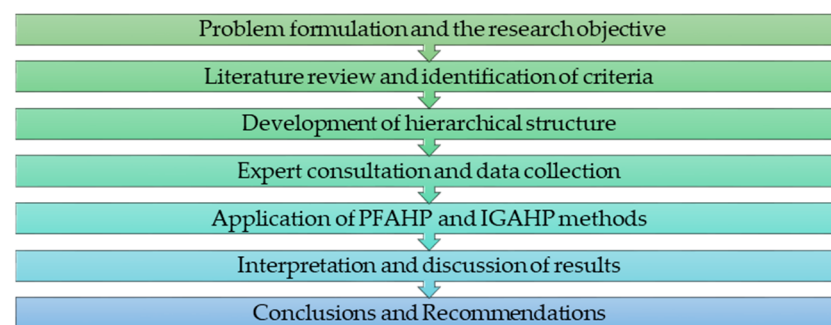


Figure 3. The methodological framework.

The following explains the methodological framework:

Problem Formulation and Research Objective: This study focused on evaluating critical components for the long-term deployment of IoT in enterprises, considering the unpredictability of the environment, to facilitate strategic planning and informed decision-making.

Literature Review and Criteria Identification: To extract and compile performance metrics used in enterprise IoT initiatives, a thorough assessment of previous IoT research was conducted. Initially, more than 40 possible indications were gathered, and Delphi rounds were used to refine them further.

Development of Hierarchical Structure: Indicators were organized hierarchically into main and sub-criteria based on their thematic relevance and interdependence. The structure was validated by senior academics and industry experts.

Expert Consultation and Data Collection: Experts from IoT-active enterprises in the manufacturing, logistics, energy, and IT sectors participated. Data were collected via structured pairwise comparison. Experts were grouped by experience and domain (technical vs. managerial). Inconsistent replies were eliminated using a consistency ratio cutoff ($CR < 0.1$).

Application of PFAHP and IGAHP: Expert feedback was examined using the two methods independently. PFAHP was used to model subjective preferences and linguistic

hesitations, and IGAHP was used to record numerical estimate uncertainty. The final ranks were calculated after applying fuzzy and grey aggregation procedures. Spearman's and Salabun similarity coefficients were used for cross-method validation.

Interpretation and Discussion of Results: The results were analyzed in terms of their strategic relevance to the implementation of IoT. The influence of indicators was discussed, and the complementary nature of the two methods was emphasized.

Conclusions and Recommendations: Important lessons learned were offered to help enterprise stakeholders. Future research prospects were explored, including the model's scalability and transferability to various organizational contexts, as well as its structure.

Building on the theoretical framework, this section outlines the methodology used to assess and prioritize the factors influencing IoT adoption. Given the complexity and uncertainty associated with evaluating subjective criteria, we apply two advanced Multi-Criteria Decision-Making (MCDM) approaches—PFAHP and IGAHP. The following subsections describe the structure of the hierarchical model, the evaluation scales, and the implementation steps of both methods.

3.2. MCDM in Application with Literature Review

The MCDM problem calls for selecting the best alternatives from various options based on several predetermined criteria. Assume $\{A_1, A_2, \dots, A_n\}$ is a finite set of alternatives. A set of criteria $\{C_1, C_2, \dots, C_m\}$ is used to evaluate the options. For every alternative $A_i \forall i = 1, 2, \dots, n$, a performance score pick is determined by the criterion $C_j \forall j = 1, 2, \dots, m$. An MCDM method ranks the alternatives from best to worst based on the computed performance scores.

The idea of fuzzy sets, first presented by Zadeh [51], has been a formal and practical tool for dealing with ambiguity, partially known knowledge, and inaccurate data in ambiguous and inconclusive real-life situations. Fuzzy sets, also known as type-1 fuzzy sets, are classical crisp set generalizations that allow elements of the universal set to have a given probability of belonging to a specific set. To do this, membership functions—often denoted by μ —that map each member of the universal set to the interval $[0, 1]$ are used. Zadeh [52] created type-2 fuzzy sets as ordinary fuzzy set generalizations with a membership function grade formed of a type-1 fuzzy set because it can be challenging to quantify uncertainty and determine the proper weight of the membership function. They are convenient when setting a membership function for a fuzzy set is difficult [53]. Intuitionistic fuzzy sets (IFSs), which have both the membership and non-membership functions, were presented by Atanasov [54]. Intuitionistic fuzzy sets of the second type [55], more recently known as Pythagorean fuzzy sets (PFSs), were introduced by Yager [56]. The sum of the squares of their membership function and non-membership function lies in the interval $[0, 1]$. They improved the preexisting circumstances and allowed the decision-makers to characterize the hazy portion of the material more thoroughly and in depth. Geometrically speaking, focusing on the first quadrant expands the surface of decision-making options from a triangle constrained by the points $(0, 0)$, $(1, 0)$, and $(0, 1)$ to the circle section. Based on this method, decision makers express their opinions regarding the support (membership) and opposition (non-membership) grades for alternative eligibility in practice. The sum of these grades of membership and non-membership may be greater than 1, and their square sum is equal to or less than 1 [57]. PFSs are incorporated into a risk assessment methodology in [58] and a superiority and inferiority ranking methodology in [57]. For MCDM issues, the Pythagorean fuzzy Technique for Order of Preference by Similarity to Ideal Solution was developed in [59,60], Pythagorean fuzzy scoring was developed in [61], and Pythagorean Fuzzy AHP was used to solve issues associated with landfill site selection and scientific education innovation platforms [62]. Using the Interval Valued Pythagorean

Fuzzy AHP, a scoring model for the smartness of public buildings was developed [63]. PFSs were applied in the development of solar technology [64], multi-criteria evaluation of cloud service providers [65], assessment of the performance of course content indicators [66], and selection of locations for waste disposal [67]. MCDM has found applications in various spheres, from AHP methods [68,69], the Fuzzy Analytical Hierarchy Process (FAHP), and Type-2 methods [70], to more recent applications [70,71].

3.3. Hierarchy Structure of IoT Effectiveness

Creating a platform for enhancing efficiency in sustainable IoT by modeling indicators is a complex task. Every company is unique, and achieving IoT efficiency in different environmental conditions is a challenge. Other domains and constitutive variables associated with successful IoT are identified by reviewing the literature.

3.3.1. Expert Involvement

When selecting indicators, an agreement was reached on the source of indicators based on the given literature. One group of experts opted for interval scoring, while another opted for a linguistic scale. Fifty-five experts from 27 companies in Serbia participated in the selection and evaluation of the indicators. Companies operate across a range of industry sectors—such as manufacturing, logistics, energy, and smart services—with a strong emphasis on ensuring that the collected data accurately represent real-world operational practices and conditions. Instead of relying on assumptions or theoretical opinions, the experts provided input based on their own experience working on IoT projects and the decision-making process within their organizations. In this way, the priorities among the indicators are established based on their practical usability, rather than theoretical assumptions.

The proposed literature served as the basis for selecting the sub-criteria. The professional profiles of the experts are shown in Figure 4a, and their work experience is shown in Figure 4b.

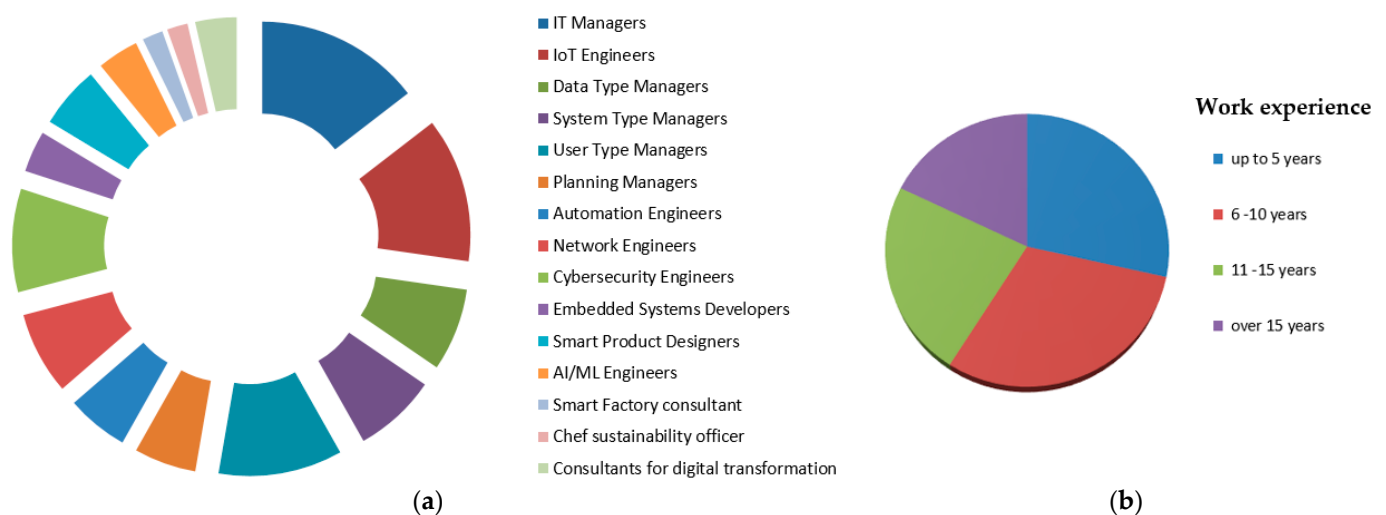


Figure 4. Expert background analysis: (a) professional profiles; (b) work experience.

Professional consultation with specialists actively utilizing IoT technologies was a component of the qualitative study. Experts were grouped based on age, education, and job experience to minimize potential bias in the assessment process and to benefit from a variety of viewpoints. These experts came from both the ICT sector and business management fields, offering balanced insights from both technical and business perspectives. The expert engagement followed these phases:

- Initial outreach and participant selection from IoT-adopting enterprises, ensuring representation across roles (technical and managerial) and domains (Figure 4a).
- Categorization by work experience to balance junior and senior perspectives (Figure 4b).
- Distribution of structured pairwise comparison questionnaires tailored to each method (PFAHP/IGAHP), along with short training materials to ensure methodological understanding.
- Independent and anonymous scoring to minimize peer influence or groupthink.
- Cross-validation by applying both methods and comparing results using Spearman's and Salabun coefficients to assess the reduction of subjectivity.

Bias Mitigation Measures were taken to lessen subjective bias and improve the validity of expert contributions throughout data gathering and analysis:

A wide range of expertise. Experts were selected to ensure a mix of practical and strategic perspectives.

- Balanced grouping (Figure 4).
- Structured guidance: All participants received methodological instructions and examples to ensure consistency in pairwise comparisons across both PFAHP and IGAHP formats.
- Consistency filtering.
- Methodological cross-checking.

3.3.2. Hierarchy Development

By examining the references according to the primary sets of indicators, we generated a hierarchical structure, as shown in Figure 5.

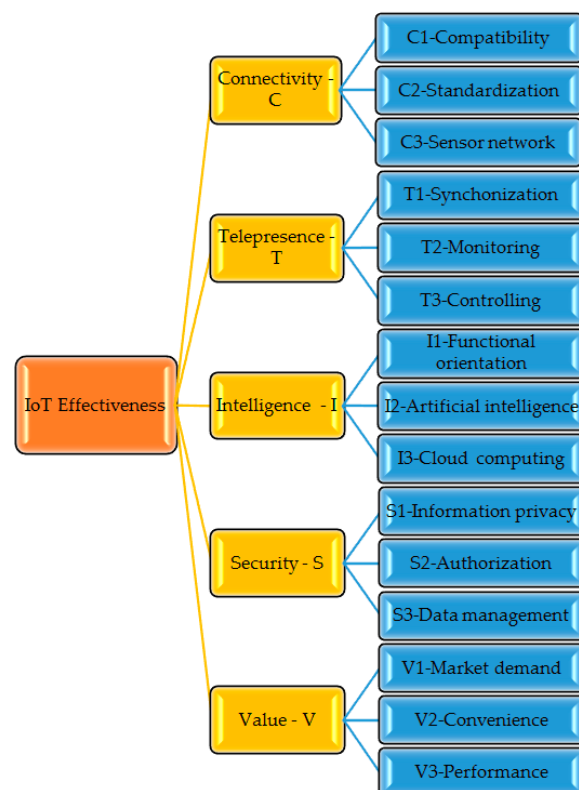


Figure 5. The effectiveness of IoT outlined in a hierarchy.

This research was conducted according to a specified research design consisting of preliminary research or an introduction to further quantitative research. Along with the

formulation of the problem, the definition of the subject, the importance and objectives of this research, the enterprise being investigated, and the structure of this research were elaborated in detail. Interviews covered the set topics and subtopics; these were followed by linguistic evaluations. The examination was conducted in accordance with the methodological (technical) rules of the interview. Information informing the experts' evaluations was obtained, taking into consideration the respondents' personalities and dignity. Given the differences in the importance of the indicators, the experts provided two assessments: linguistic and interval. The experts' choices between these two approaches are provided in the methodology.

We utilized the experts' responses and judgments to construct pairwise comparison matrices necessary for both PFAHP and IGAHP methods. These empirical data were utilized to make the decision model more applicable and realistic for the practical validation of the proposed framework. Criteria for expert selection included established experience with IoT implementation or strategic planning in enterprise environments.

3.4. Pythagorean Fuzzy Analytical Hierarchy Process (PFAHP)

As a fuzzy set generalization, the Pythagorean fuzzy set proposed by Yager [56] considers membership and non-membership. The proposed Pythagorean fuzzy analytic hierarchy method is presented through the following phases: linguistic evaluation and weights in fuzzy numbers. In the first phase, the experts must rate their opinion on the dimensions against the identified indicators according to the problem. Experts were asked to rate the pairwise comparison of fuzzy AHP on a five-point scale. The use of five-point linguistic scales is widespread in the application of such methods. It is associated with a person's ability to easily distinguish five degrees on a scale. The linguistic variables are presented in Table 3. Then, decision-makers (DMs) are asked to provide a rating using Pythagorean fuzzy number linguistic scales defined by the two parameters of PFN (membership and non-membership functions).

Table 3. Linguistic terms and evaluation scale in Pythagorean fuzzy sets.

Linguistic Terms	Evaluating Scale in Pythagorean Fuzzy Sets
Absolutely weak dominance	$\langle 0.1, 0.9 \rangle$
Extremely weak dominance	$\langle 0.2, 0.8 \rangle$
Very weak dominance	$\langle 0.3, 0.7 \rangle$
Fairly weak dominance	$\langle 0.4, 0.6 \rangle$
Equal importance	$\langle 0.5, 0.4 \rangle$
Fairly strong dominance	$\langle 0.6, 0.4 \rangle$
Very strong dominance	$\langle 0.7, 0.3 \rangle$
Extremely strong dominance	$\langle 0.8, 0.2 \rangle$
Absolutely strong dominance	$\langle 0.9, 0.1 \rangle$

Let A be a fixed set, then a Pythagorean fuzzy set (PFS) $\tilde{P}$ is an object with the following form (Equation (1)):

$$\tilde{P} = \{ \langle a, \mu_{\tilde{P}}(a), \nu_{\tilde{P}}(a) \rangle, a \in A \}, \quad (1)$$

where $\mu_{\tilde{P}}(a) : A \rightarrow [0, 1]$ denotes the degree of membership and $\nu_{\tilde{P}}(a) : A \rightarrow [0, 1]$ denotes the degree of non-membership of the element $a \in A$ to the set $\tilde{P}$ and satisfies (Equation (2)):

$$0 \leq (\mu_{\tilde{P}}(a))^2 + (\nu_{\tilde{P}}(a))^2 \leq 1. \quad (2)$$

The pair $\langle \mu_{\tilde{p}}, \nu_{\tilde{p}} \rangle$ is called a Pythagorean fuzzy number (PFN), with the degree of indeterminacy defined by Equation (3).

$$\mathcal{I}_{\tilde{p}} = \sqrt{1 - \left((\mu_{\tilde{p}}(a))^2 + (\nu_{\tilde{p}}(a))^2 \right)}. \quad (3)$$

The geometric interpretation of the space of a Pythagorean membership grade is provided in Figure 6.

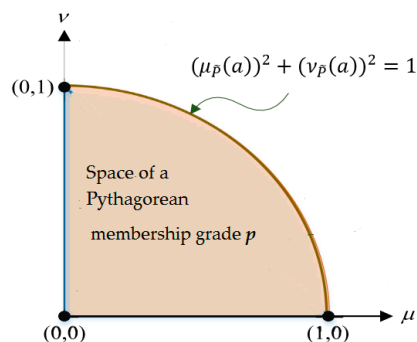


Figure 6. Spaces of Pythagorean membership grade of two PFNs.

Definition 1. For any two PFS, $\tilde{P}_1 = \langle \mu_{\tilde{P}_1}, \nu_{\tilde{P}_1} \rangle$, $\tilde{P}_2 = \langle \mu_{\tilde{P}_2}, \nu_{\tilde{P}_2} \rangle$ and $c > 0$, the basic operations are defined by Equations (4)–(7).

$$\tilde{P}_1 \oplus \tilde{P}_2 = \langle \mu_{\tilde{P}_1}, \nu_{\tilde{P}_1} \rangle \oplus \langle \mu_{\tilde{P}_2}, \nu_{\tilde{P}_2} \rangle = \left\langle \left(\mu_{\tilde{P}_1}^2 + \mu_{\tilde{P}_2}^2 - \mu_{\tilde{P}_1}^2 \mu_{\tilde{P}_2}^2 \right)^{\frac{1}{2}}, \nu_{\tilde{P}_1} \nu_{\tilde{P}_2} \right\rangle, \quad (4)$$

$$\tilde{P}_1 \otimes \tilde{P}_2 = \langle \mu_{\tilde{P}_1}, \nu_{\tilde{P}_1} \rangle \otimes \langle \mu_{\tilde{P}_2}, \nu_{\tilde{P}_2} \rangle = \left\langle \mu_{\tilde{P}_1} \mu_{\tilde{P}_2}, \left(\nu_{\tilde{P}_1}^2 + \nu_{\tilde{P}_2}^2 - \nu_{\tilde{P}_1}^2 \nu_{\tilde{P}_2}^2 \right)^{\frac{1}{2}} \right\rangle, \quad (5)$$

$$c \odot \tilde{P}_1 = c \odot \langle \mu_{\tilde{P}_1}, \nu_{\tilde{P}_1} \rangle = \left\langle \left(1 - \left(1 - \mu_{\tilde{P}_1}^2 \right)^c \right)^{1/2}, \nu_{\tilde{P}_1}^c \right\rangle, \quad (6)$$

$$\tilde{P}_1^c = \left\langle \mu_{\tilde{P}_1}^c, \left(1 - \left(1 - \nu_{\tilde{P}_1}^2 \right)^c \right)^{1/2} \right\rangle. \quad (7)$$

Definition 2. A score function, defined to compare the magnitude of two PFNs, is presented in Equation (8).

$$s(\tilde{P}) = (\mu_{\tilde{P}})^2 - (\nu_{\tilde{P}})^2 \quad (8)$$

Definition 3. The accuracy function, defined to compare the magnitude of two PFNs, is presented in Equation (9).

$$\alpha(\tilde{P}) = (\mu_{\tilde{P}})^2 + (\nu_{\tilde{P}})^2 \quad (9)$$

The PFAHP method can be expressed as follows [63]:

- (1) The MCDM problem is generated in a hierarchical structure with a defined goal.
- (2) The comparison matrix shows a pairwise comparison of the criteria based on the DMs' preferences. The definition in Table 2 is used to build the relevant comparison matrices.

- (3) Apply Saaty's classic consistency analysis to determine the comparison matrix's consistency. Each pairwise comparison matrix is examined for consistency using the matrix consistency indexes $CI = \frac{\lambda_{max} - n}{n-1}$ and $CR = \frac{CI}{RI}$, where λ_{max} is the matrix's largest eigenvalue, and RI is the random index. The $CI < 0.1$ is suitable; if not, experts should reevaluate their conclusions to make them more consistent.
- (4) Fuzzy weights of each criterion and global fuzzy weights are calculated. By multiplying the values for each criterion using Equation (5), the geometric mean for each row is determined. Then, the root values are calculated by applying Equation (7).
- (5) The defuzzification process is conducted using Formula (10).

$$def(\tilde{P}) = \frac{1 - (v_{\tilde{P}})^2}{2 - (\mu_{\tilde{P}})^2 - (v_{\tilde{P}})^2} \quad (10)$$

The PFAHP method has the following advantages:

- Compared to the ordinary fuzzy AHP, the Pythagorean AHP allows for greater freedom in expressing the degree of certainty and uncertainty.
- It enables the expression of more complex expert opinions, especially when the opinions are uncertain or conflicting. The modeling of expert ratings is more precise.
- When experts cannot agree, Pythagorean fuzzy numbers enable the expression of differences in certainty.
- Multidimensional thought processing enables the use of multiple experts with varying degrees of expertise.

3.5. Interval Grey Analytical Hierarchy Process (IGAHP) Method

One way to overcome the shortcomings of the AHP method is to combine the application of intervals and AHP methods by using interval comparison matrices in pairs in the AHP technique and the application of the IAHP method.

IGAHP is an extension of the classical Analytic Hierarchy Process (AHP) that utilizes grey theory and interval values to enhance the handling of uncertainty and imprecision in decision-making, particularly when subjective expert judgment is involved. This method is mostly used in multi-criteria decision-making (MCDM) when the data are incomplete or imprecise, and expert ratings are given as intervals, which introduces ambiguity in preferences between criteria.

An interval grey number is an interval, defined by Equation (11).

$$a_{\otimes} = [a^l, a^r] = \{a \mid a^l \leq a \leq a^r\}. \quad (11)$$

The main characteristic of $a_{\otimes}$ is that its exact value is unknown. The only known information is the range where the value lies.

Definition 4. For two interval grey numbers $a_{\otimes} = [a^l, a^r]$ and $b_{\otimes} = [b^l, b^r]$ and scalar $\lambda > 0$, the basic operations are defined as follows:

- Addition: $a_{\otimes} \oplus b_{\otimes} = [a^l + b^l, a^r + b^r]$,
- Subtraction: $a_{\otimes} \ominus b_{\otimes} = [a^l - b^r, a^r - b^l]$,
- Multiplication: $a_{\otimes} \odot b_{\otimes} = [a^l b^l, a^r b^r]$,
- Inverse: $a_{\otimes}^{-1} = [1/a^r, 1/a^l]$,
- Division: $a_{\otimes} \oslash b_{\otimes} = a_{\otimes} \odot b_{\otimes}^{-1} = [a^l/b^r, a^r/b^l]$,
- Scalar multiplication: $\lambda a_{\otimes} = [\lambda a^l, \lambda a^r]$.

Interval grey numbers are presented in [72,73]. Even in the case of the opinion of only one expert, that expert often cannot decide on a specific numerical value that would express their position on the dominance of one criterion over another. The problem becomes more significant when multiple experts from various professions are involved, and the issue is multidimensional. To overcome these problems, instead of using classic comparison matrices, interval comparison matrices can be used $[a^l, a^r]$, $a^l \leq a^r$, where a^l represents the lower limit and a^r represents the upper limit. Some interval mathematics algorithms can be found in [74,75].

The IGAHP method can be expressed as follows:

- (1) The general goal definition and identification, and the hierarchical structure formation through the criteria and sub-criteria identification contribute to the general goal (Equation (12)).
- (2) The comparison judgment matrix C_{int} creation [76]:

$$C_{int} = \begin{bmatrix} 1 & [x_{12}, y_{12}] & \cdots & [x_{1n}, y_{1n}] \\ [x_{21}, y_{21}] & 1 & \cdots & [x_{2n}, y_{2n}] \\ \vdots & \vdots & \ddots & \vdots \\ [x_{n1}, y_{n1}] & [x_{n2}, y_{n2}] & \cdots & 1 \end{bmatrix}. \quad (12)$$

In the matrix C_{int} , for all $j = \overline{1, n}$, $x_{ij} \leq y_{ij}$, $x_{ij} \geq 0$, $y_{ij} \geq 0$, $x_{ji} = 1/y_{ij}$ and $y_{ji} = 1/x_{ij}$.

- (3) The consistency of matrix C_{int} examination. Based on the matrix C_{int} , non-interval matrices $R = (r_{ij})_{n \times n}$, $S = (s_{ij})_{n \times n}$ and $T = (t_{ij})_{n \times n}$, $0 \leq \varepsilon \leq 1$, are constructed and presented by Equations (13)–(15).

$$R = \begin{bmatrix} 1 & y_{12} & \cdots & y_{1n} \\ x_{21} & 1 & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & 1 \end{bmatrix}, \quad (13)$$

$$S = \begin{bmatrix} 1 & x_{12} & \cdots & x_{1n} \\ y_{21} & 1 & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{n1} & y_{n2} & \cdots & 1 \end{bmatrix}, \quad (14)$$

$$T = \begin{bmatrix} 1 & y_{12}^\varepsilon \cdot x_{12}^{1-\varepsilon} & \cdots & y_{1n}^\varepsilon \cdot x_{1n}^{1-\varepsilon} \\ x_{21}^\varepsilon \cdot y_{21}^{1-\varepsilon} & 1 & \cdots & y_{2n}^\varepsilon \cdot x_{2n}^{1-\varepsilon} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1}^\varepsilon \cdot y_{n1}^{1-\varepsilon} & x_{n2}^\varepsilon \cdot y_{n2}^{1-\varepsilon} & \cdots & 1 \end{bmatrix}. \quad (15)$$

The consistency of the matrix C_{int} is examined by checking the consistency of introduced non-interval matrices R and S . If matrices R and S are consistent and meet the condition $CR \leq 0.1$, then the interval matrix C_{int} is also consistent.

- (4) Determination of interval matrix weighting vectors. The convex combination method is used to calculate interval matrix C_{int} weights [77]. Let $w(T) = (w_1(T), w_2(T), \dots, w_n(T))^T$ is a vector containing the weights of a matrix T , then $w_i(T) = \left(\prod_{j=1}^n t_{ij} \right)^{1/n}$, for all $i = \overline{1, n}$ and all $0 \leq \varepsilon \leq 1$.

- (5) Determination of the probability matrix of preferences $P = (p_{ij})_{n \times n}$. Let $[w_i^1, w_i^2]$ and $[w_j^1, w_j^2]$ be two intervals. Then,

$$s_{ij} = \begin{cases} 1, & w_i^1 \geq w_j^2, \\ 0, & w_j^1 \geq w_i^2, \\ \frac{(w_i^2 - w_j^1)^2}{2}, & w_j^1 \geq w_i^1 \text{ and } w_j^2 \geq w_i^2, \\ (w_i^2 - w_j^2)(w_j^2 - w_j^1) + \frac{(w_j^2 - w_i^1)^2}{2}, & w_j^1 \geq w_i^1 \text{ and } w_j^2 < w_i^2, \\ (w_i^2 - w_i^1)(w_i^1 - w_j^1) + \frac{(w_i^2 - w_i^1)^2}{2}, & w_j^1 < w_i^1 \text{ and } w_j^2 \geq w_i^2, \\ (w_i^2 - w_i^1)(w_j^2 - w_j^1) - \frac{(w_j^2 - w_i^1)^2}{2}, & w_j^1 < w_i^1 \text{ and } w_j^2 < w_i^2 \end{cases} \quad (16)$$

and $s_{ij}^* = (w_i^2 - w_i^1)(w_j^2 - w_j^1)$. Using Equation (16), we obtained the probability p_{ij} that interval $[w_i^1, w_i^2]$ is bigger than interval $[w_j^1, w_j^2]$ by $p_{ij} = s_{ij}/s_{ij}^*$.

Interval weights are ranked using the row–column elimination method according to the obtained probability matrix [78]. Fuzzy and interval approaches can be used in more ways when using MCDM [79,80].

With the IGAHP method, respondents are expected to give an interval value of the liking rating, which is much easier than deciding on a specific value. With the PFAHP method, respondents are allowed to determine how much they like or dislike each statement (which is a novelty). The use of five-point linguistic scales is the most widespread in the application of such methods, and it is associated with the possibility of a person being able to distinguish five degrees on a scale with great ease. Using a combination of these two methods and comparing their rankings was introduced to overcome potential biases in expert judgments and scalability challenges of the proposed model.

Advantages of the IGAHP method:

- Imprecision robustness—instead of forcing exact values, it embraces uncertainty.
- Better reflects expert opinion—experts can provide approximate values.
- Suitable for complex decisions—especially when there are multiple experts and differences in opinion.
- Flexibility—can be combined with other methods.

Figure 7 shows a graphic representation of these algorithms.

Following the previously defined methodological setting, this research continued with consistent application of the PFAHP and IGAHP methods within the framework of the developed hierarchical model. The criteria were evaluated and weighted. In the following section, the results of applying the model will be presented, including the obtained priority values and their significance for strategic decision-making in the context of IoT implementation.

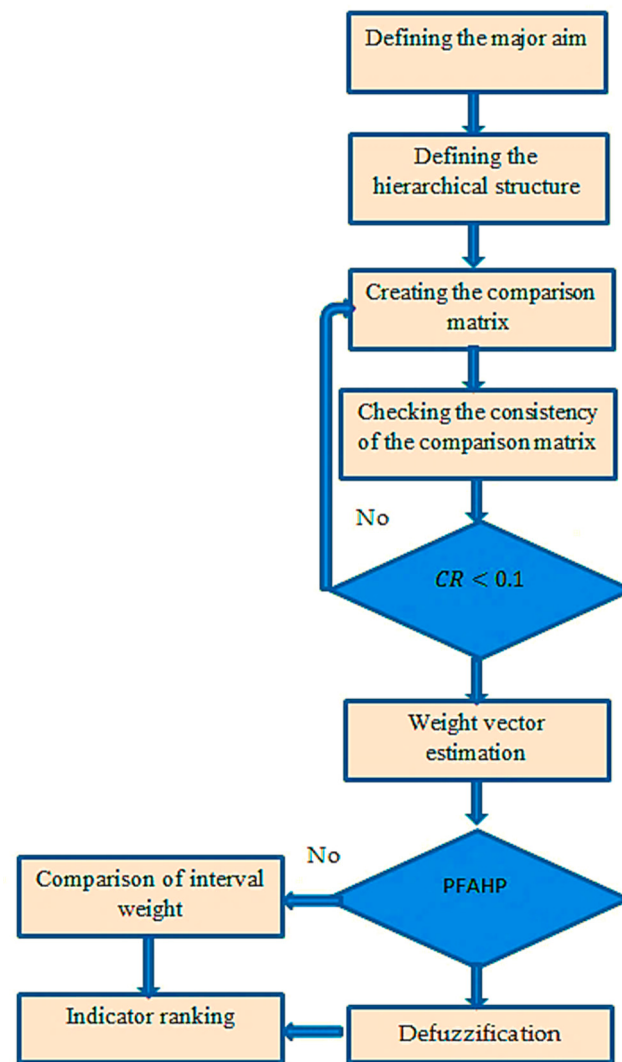


Figure 7. Block representation of the algorithms.

4. Results and Discussion

This study uses two approaches for the investigation. The AHP (fuzzy and interval grey method) is suitable for MCDM problems when it is difficult to precisely quantify the impact of criteria on decision problems. With the introduction and execution of PFAHP and IGAHP methods, the subjective aspects that dominate the decision-making process are reduced, making the prioritization process more transparent.

In this section, we apply the algorithms described in Sections 3.3 and 3.4. All comparison matrices have been created based on the opinions of experts in the IoT and entrepreneurship fields, and are consistent. The experts determined how the criteria and sub-criteria were compared. Business experts agreed on the interval approach, whereas experts from the ICT and scientific domains employed the PFAHP method in the evaluation of IoT.

The results obtained using the PFAHP method are presented in Tables 4–9. The weights of the indicators are marked by w_c and the sub-factors by w_{sc} .

Table 4. Comparison matrix and weights for the main criteria in the PFAHP (CI = 0.0139109, CR = 0.0124204).

	S	V	C	T	I	w_c
S	$\langle 0.5, 0.4 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	$\langle 0.7, 0.3 \rangle$	$\langle 0.7, 0.3 \rangle$	0.230631
V	$\langle 0.5, 0.4 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	$\langle 0.7, 0.3 \rangle$	$\langle 0.7, 0.3 \rangle$	0.225179
C	$\langle 0.4, 0.6 \rangle$	$\langle 0.4, 0.6 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	0.200522
T	$\langle 0.3, 0.7 \rangle$	$\langle 0.3, 0.7 \rangle$	$\langle 0.4, 0.6 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.5, 0.4 \rangle$	0.174533
I	$\langle 0.3, 0.7 \rangle$	$\langle 0.3, 0.7 \rangle$	$\langle 0.4, 0.6 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.5, 0.4 \rangle$	0.169135

Table 5. Comparison matrix and weights for the sub-criterion S in the PFAHP (CI = 0, CR = 0).

	S ₁	S ₂	S ₃	w_{sc}
S ₁	$\langle 0.5, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	0.364275
S ₂	$\langle 0.4, 0.6 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.5, 0.4 \rangle$	0.325444
S ₃	$\langle 0.4, 0.6 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.5, 0.4 \rangle$	0.310281

Table 6. Comparison matrix and weights for the sub-criterion V in the PFAHP (CI = 0, CR = 0).

	V ₁	V ₂	V ₃	w_{sc}
V ₁	$\langle 0.5, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	0.364275
V ₂	$\langle 0.4, 0.6 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.5, 0.4 \rangle$	0.325444
V ₃	$\langle 0.4, 0.6 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.5, 0.4 \rangle$	0.310281

Table 7. Comparison matrix and weights for the sub-criterion C in the PFAHP (CI = 0.0192555, CR = 0.0331992).

	C ₃	C ₂	C ₁	w_{sc}
C ₃	$\langle 0.5, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	$\langle 0.7, 0.3 \rangle$	0.37962
C ₂	$\langle 0.4, 0.6 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	0.33352
C ₁	$\langle 0.3, 0.7 \rangle$	$\langle 0.4, 0.6 \rangle$	$\langle 0.5, 0.4 \rangle$	0.28686

Table 8. Comparison matrix and weights for the sub-criterion I in the PFAHP (CI = 0.0192555, CR = 0.0331992).

	I ₂	I ₁	I ₃	w_{sc}
I ₂	$\langle 0.5, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	$\langle 0.7, 0.3 \rangle$	0.37962
I ₁	$\langle 0.4, 0.6 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.6, 0.4 \rangle$	0.33352
I ₃	$\langle 0.3, 0.7 \rangle$	$\langle 0.4, 0.6 \rangle$	$\langle 0.5, 0.4 \rangle$	0.28686

Table 9. Comparison matrix and weights for the sub-criterion T in the PFAHP (CI = 0.0192555, CR = 0.0331992).

	T ₁	T ₂	T ₃	w_{sc}
T ₁	$\langle 0.5, 0.4 \rangle$	$\langle 0.7, 0.3 \rangle$	$\langle 0.6, 0.4 \rangle$	0.37962
T ₂	$\langle 0.3, 0.7 \rangle$	$\langle 0.5, 0.4 \rangle$	$\langle 0.4, 0.6 \rangle$	0.33352
T ₃	$\langle 0.4, 0.6 \rangle$	$\langle 0.6, 0.4 \rangle$	$\langle 0.5, 0.4 \rangle$	0.28686

Figure 8 graphically displays the weights of the sub-criteria.

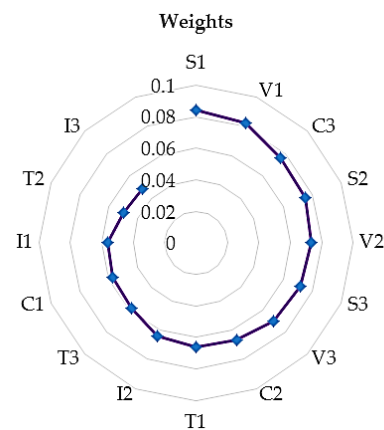


Figure 8. Graphic representation of sub-criteria weights for the PFAHP method.

The results obtained using the IGAHP method are presented in Tables 10–15. The interval matrix proposed by the experts is consistent because matrices R and S are consistent.

Table 10. Interval comparison matrix and interval weights of criteria in the IGAHP method ($CI_R = 0.00984433$, $CR_R = 0.00878958$, $CI_S = 0.0279004$, $CR_S = 0.0249111$).

	S	V	C	T	I	w_c
S	[1, 1]	[1, 2]	[2, 2]	[3, 4]	[3, 5]	[1.78649, 2.39616]
V	[1/2, 1]	[1, 1]	[1, 2]	[3, 3]	[3, 4]	[1.55665, 1.6578]
C	[1/2, 1/2]	[1/2, 1]	[1, 1]	[2, 3]	[2, 4]	[1.15826, 1.25091]
T	[1/4, 1/3]	[1/3, 1/3]	[1/3, 1/2]	[1, 1]	[1, 2]	[0.557189, 0.557194]
I	[1/5, 1/3]	[1/4, 1/3]	[1/4, 1/2]	[1/2, 1]	[1, 1]	[0.361175, 0.557189]

Table 11. Interval comparison matrix and interval weights of sub-criteria S in the IGAHP method ($CI_R = 0$, $CR_R = 0$, $CI_S = 0.00460136$, $CR_S = 0.00793337$).

	S ₁	S ₃	S ₂	w_{sc}
S ₁	[1, 1]	[2, 2]	[2, 3]	[1.5874, 1.81712]
S ₃	[1/2, 1/2]	[1, 1]	[1, 2]	[0.793701, 1]
S ₂	[1/3, 1/2]	[1/2, 1]	[1, 1]	[0.550321, 0.793701]

Table 12. Interval comparison matrix and interval weights of sub-criteria V in the IGAHP method ($CI_R = 0$, $CR_R = 0$, $CI_S = 0.00460136$, $CR_S = 0.00793337$).

	V ₁	V ₃	V ₂	w_{sc}
V ₁	[1, 1]	[2, 2]	[2, 3]	[1.5874, 1.81712]
V ₃	[1/2, 1/2]	[1, 1]	[1, 2]	[0.793701, 1]
V ₂	[1/3, 1/2]	[1/2, 1]	[1, 1]	[0.550321, 0.793701]

Table 13. Interval comparison matrix and interval weights of sub-criteria C in the IGAHP method ($CI_R = 0.0268108$, $CR_R = 0.0462255$, $CI_S = 0.0268108$, $CR_S = 0.0462255$).

	C ₃	C ₂	C ₁	w_{sc}
C ₃	[1, 1]	[1, 2]	[2, 2]	[1.25992, 1.5874]
C ₂	[1/2, 1]	[1, 1]	[1, 2]	[1, 1]
C ₁	[1/2, 1/2]	[1/2, 1]	[1, 1]	[0.629961, 0.793701]

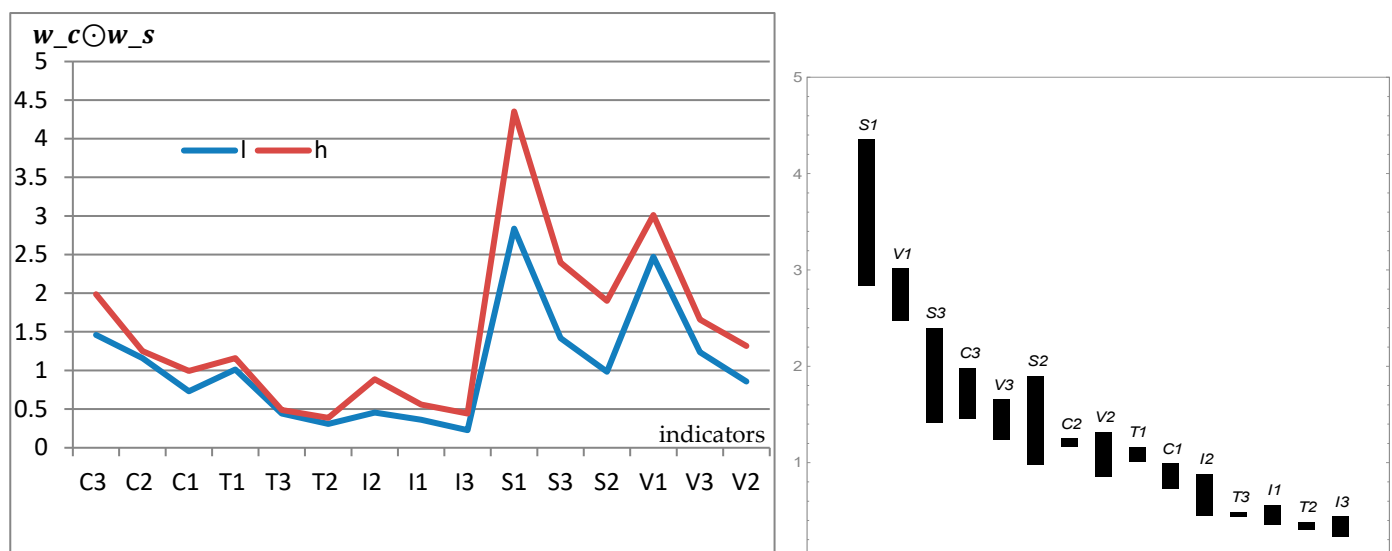
Table 14. Interval comparison matrix and interval weights of sub-criteria I in the IGAHP method ($CI_R = 0.0268108$, $CR_R = 0.0462255$, $CI_S = 0.0268108$, $CR_S = 0.0462255$).

	I_2	I_1	I_3	w_{sc}
I_2	[1, 1]	[1, 2]	[2, 2]	[1.25992, 1.5874]
I_1	[1/2, 1]	[1, 1]	[1, 2]	[1, 1]
I_3	[1/2, 1/2]	[1/2, 1]	[1, 1]	[0.629961, 0.793701]

Table 15. Interval comparison matrix and interval weights of sub-criteria T in the IGAHP method ($CI_R = 0.00914735$, $CR_R = 0.0157713$, $CI_S = 0.0268108$, $CR_S = 0.0462255$).

	T_1	T_2	T_3	w_{sc}
T_1	[1, 1]	[2, 3]	[3, 3]	[1.81712, 2.08008]
T_2	[1/3, 1/2]	[1, 1]	[1, 2]	[0.793701, 0.87358]
T_3	[1/3, 1/3]	[1/2, 1]	[1, 1]	[0.550321, 0.693361]

Let l denote the lower limit and h denote the upper limit of interval weights. Figure 9a shows the interval weights of the indicators, and Figure 9b shows the final ranking of the indicators using the IGAHP method.



l —lower limit of interval weights; h —upper limit of interval weights

(a)

(b)

Figure 9. (a) The interval weights of the indicators and (b) the final ranking of the indicators based on the IGAHP method.

Interval assessment assigns equal weights to all values from the expert-selected intervals, but the Pythagorean fuzzy techniques assign more weight to central values. Table 16 contains the final rankings of indicators using the PFAHP and IGAHP methods.

Table 16. Ranking of indicators with final weights, final interval weights, and probability based on the PFAHP and IGAHP methods.

Ranking PFAHP	Weight	Ranking IGAHP	$w_c \odot w_{sc}$	p
S ₁	0.084013	S ₁	[2.83587, 4.35411]	0.981039
V ₁	0.082027	V ₁	[2.47103, 3.01242]	1
C ₃	0.076122	S ₃	[1.41794, 2.39616]	0.688659
S ₂	0.075057	C ₃	[1.45931, 1.98569]	0.911379
V ₂	0.073283	V ₃	[1.23551, 1.6578]	0.504539
S ₃	0.071560	S ₂	[0.98314, 1.90183]	0.758956
V ₃	0.069869	C ₂	[1.15826, 1.25091]	0.757775
C ₂	0.066878	V ₂	[0.85666, 1.3158]	0.501056
T ₁	0.066256	T ₁	[1.01248, 1.15901]	1
I ₂	0.064207	C ₁	[0.72966, 0.99285]	0.893962
T ₃	0.058210	I ₂	[0.45505, 0.88448]	0.973713
C ₁	0.057522	T ₃	[0.44224, 0.48675]	0.52709
I ₁	0.056410	I ₁	[0.36118, 0.55719]	0.979742
T ₂	0.050067	T ₂	[0.30663, 0.38634]	0.554026
I ₃	0.048518	I ₃	[0.22753, 0.44224]	

Comparing ranked indicators involves analyzing the different ranks, scores, or values of indicators to determine their relative positions, importance, or relationships. Depending on the nature of the data, several methods are used to compare ranks. Spearman's rank correlation is a non-parametric technique used to determine the degree and direction of association between two ranked datasets. This method is employed when dealing with ordinal (ranked) data or data that are not regularly distributed. We used Spearman's rank correlation coefficient to compare the lists of ranked sub-criteria generated using the PFAHP and IGAHP methods [81], as per Equation (17).

$$C_s = 1 - \frac{6 \sum_{i=1}^n (C_{x_i} - C_{y_i})^2}{n(n^2 - 1)}. \quad (17)$$

There are n elements ranked in total, and the ranks of element i in the compared rankings are C_{x_i} and C_{y_i} . Salabun similarity ranking is a specific approach for rank comparison that was developed to analyze the similarity between different ranking methods or ranked datasets. This method is used to assess the similarity between two rankings, specifically how well they align in terms of the relative order of the objects or factors being ranked. Salabun SW coefficient was utilized to analyze the ranking similarity [82] following Equation (18):

$$C_{SW} = 1 - \sum_{i=1}^n \left(2^{-C_{x_i}} \frac{|C_{x_i} - C_{y_i}|}{\max\{|1 - C_{x_i}|, |n - C_{y_i}|\}} \right), \quad (18)$$

Based on the formulas, the indices of agreement obtained for the PFAHP and IGAHP methods are $C_s = 0.939287$, $C_{SW} = 0.950407$. The listed coefficients indicate good agreement between the ranks of these two methods. The consistent application of the PFAHP and IGAHP methods, as the most influential indicators for efficiency in sustainable IoT enterprises, highlights the importance of information privacy and market demand. For IoT to be sustainable in enterprises, information privacy is a primary guideline due to the vast amount of personal data collected. From the outset, entrepreneurs must prioritize data protection by implementing strong encryption and authentication and conducting regular security audits. Navigating the complex legal landscape surrounding data privacy is also essential. Ensuring sustainable growth and fostering consumer trust require robust

security protocols and adherence to privacy laws. Because it influences production and helps direct competition in the market, market demand has an impact on both consumers and businesses. Vendors can capitalize on future growth prospects and align their sales efforts with industry and regional trends by leveraging market information and projections. Adopters can make well-informed decisions about their IoT investments and plans by monitoring market trends, drivers, and growth projections. Significant indicators of gains from PFAHP are sensor networks, authorization, convenience, and data management. The differences in the interval approach are that the sequence is somewhat different; these are, in order of importance, data management, sensor networks, performance, and authorization. In contrast to IGAHP, which promotes data management, the PFAHP technique favors authorization. The differences in the final ranks between the IGAHP and the PFAHP methods are due to different evaluation approaches. The least influential indicators are functional orientation, monitoring, and cloud computing.

Improving efficiency in a sustainable IoT enterprise enables IoT technologies to achieve lower resource consumption, faster and more accurate operations, waste reduction, and cost optimization, all while preserving environmental and social standards. To measure efficiency not only by speed and profit, but also by how smartly and responsibly an enterprise uses IoT to improve sustainability and competitiveness, we developed an integrated model that incorporates the identified influential factors based on the final rankings obtained, as shown in Figure 10.

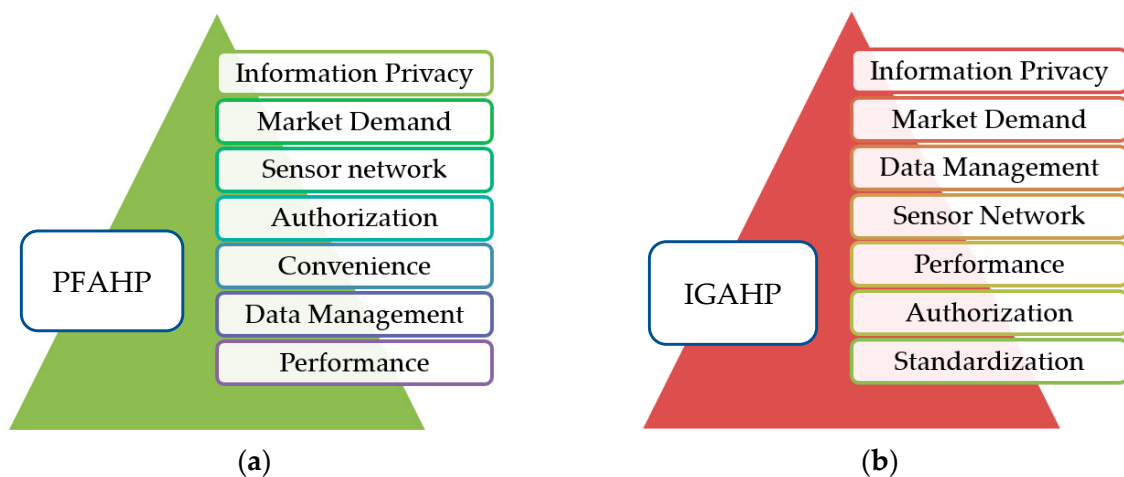


Figure 10. Influential factors as the basis for IoT efficiency in sustainable enterprises based on (a) the PFAHP method and (b) the IGAHP method.

In addition to the two primary indicators, sensor network, authorization, convenience, data management, and performance are key factors in achieving IoT system efficiency in enterprises. Each of these factors directly affects the overall functionality of the IoT solution, enabling better data collection, analysis, and management, as well as improving security and user experience.

Considering the influential factors, creating a platform for a successful IoT business requires the following key tasks:

- Companies should take certain steps to improve information privacy in IoT systems. To ensure that data transmitted from IoT devices cannot be intercepted or modified, end-to-end encryption should be used. Cloud services or on-premises servers that comply with data protection regulations should be used. Additionally, measures should be implemented to collect only necessary information, thereby reducing the likelihood of sensitive data leaks.

- Increased market competitiveness may influence how businesses deploy IoT technologies. Data analytics enables IoT devices to collect extensive information about consumers, markets, and operations. Businesses can better understand user wants and react to demand changes more rapidly by evaluating these data; additionally, increased flexibility through the use of IoT devices enables companies to adjust production, distribution, and logistics processes swiftly based on real-time market data.
- The sensor network is the heart of an IoT system. To improve the efficiency of an IoT system, sensor optimization requires the use of high-quality, low-power sensors that provide accurate and relevant data. For scalability, a company needs planar networks that can be easily expanded to include new IoT devices and sensors as the business grows.
- Authorization and access control are essential for protecting and securing data. To provide safe access to devices and data, multi-factor authentication must be used. Employee roles and responsibilities should be specified to provide regulated access to sensitive data. Regularly updating security protocols involves maintaining up-to-date protection and audit protocols to ensure constant system security.
- IoT solutions should be easy to implement and use. It is necessary to develop a simple interface for end-users and administrators, allowing them to easily manage and interpret the data. Tools for easy monitoring of device operation, as well as quick problem-solving (such as automatic warnings of malfunctions or device crashes), should be provided.
- High performance in IoT systems is largely dependent on efficient data handling. Analysis and reporting should be made easier with the use of data in centralized databases. Real-time data analysis technologies must be implemented to facilitate prompt decision-making in business operations. This requires investing in technologies for cleaning and validating data to avoid errors that can affect analysis and decision-making.
- For businesses to optimize network resources and enhance IoT device performance, they must select protocols and architectures that strike a balance between speed and reliable data transfer. To manage the load effectively, infrastructure overload should be avoided, the best possible resource allocation should be enabled, and scalable systems and cloud resources should be implemented. Additionally, to enable autonomous system performance modifications, integration with machine learning and artificial intelligence is required.
- Data management includes its proper life cycle. Data should be backed up regularly, and old data should be archived to ensure business continuity. Data must comply with all legislative and regulatory requirements related to their storage and processing.
- Standardization of IoT systems enables easier interoperability and reduces complexity. Standardized protocols should be used to facilitate the interoperability of devices from different manufacturers. It is necessary to commit to industry standards and certifications.

Several studies emphasize the importance of integrating IoT technology into industrial systems to enhance productivity, reduce resource consumption, and improve operational efficiency. For example, it was demonstrated in [83] that an Internet of Things system with a multi-layered design and real-time analytics has a direct impact on operational efficiency and sustainability. Similarly, an IoT system for monitoring and analyzing energy consumption and environmental parameters was developed in [84]. The results confirm the possibility of optimization through intelligent management, demonstrating real savings in energy costs and improvement of environmental parameters.

The authors of [85] conducted research using Japanese manufacturing enterprises as an example to evaluate the impact of IoT investments. The study claimed that investments in IoT led to quantifiable improvements in operational and financial efficiency, as well as faster amortization. In support of this viewpoint, the authors of [86] demonstrated that IoT monitoring enables the analysis of energy trends and recommended production management to optimize operational parameters.

Numerous metrics, including energy efficiency, equipment availability, production precision, return on investment, and the quality of a company's decisions, can be used to measure the effects of IoT adoption. Therefore, by applying methods such as PFAHP and IGAHP, it is possible to systematically evaluate and rank relevant indicators that support decision-making towards the digital and sustainable transformation of enterprises.

Most studies focus on specific applications of IoT systems in enterprises and industrial environments. Compared to these approaches, the application of PFAHP and IGAHP methodologies provides a structured, multi-criteria framework for identifying and prioritizing IoT performance indicators in enterprises. While the studies above analyze the effects of IoT through practical case studies, PFAHP and IGAHP facilitate a systematic and analytical assessment of various criteria under uncertainty, thereby contributing to more reliable decision-making in the strategic management of IoT infrastructure.

The reliability and credibility of indicator rankings were enhanced by the hybrid use of PFAHP and IGAHP, which yielded complementary insights. The framework enabled a deeper understanding of the factors that most significantly impact IoT success in business environments by integrating two methods for modeling uncertainty.

Although this study does not present individual company case studies in narrative form, the framework was validated through real-world consultations with subject matter experts who provided input based on their companies' specific IoT strategies and challenges. This type of integrated empirical evaluation enhances the credibility and applicability of the suggested model in various business contexts. The practical value of the hybrid PFAHP–IGAHP approach is enhanced by consistent prioritization patterns across sectors, which further validates that the identified indicators are context-sensitive and generalizable.

The significant degree of agreement between the two methodologies validates the robustness of the proposed hybrid framework and further confirms the set priorities. The approach's strength lies in its ability to offer multiple perspectives on uncertainty, in addition to its numerical consistency. When assessing subjective factors such as convenience, perceived value, or information privacy, a PFAHP approach is necessary to capture linguistic ambiguity and complex expert preferences adequately. By better managing incomplete data and structural ambiguity, the IGAHP technique offers greater clarity in data-driven indications, such as market demand or data governance.

The proposed framework enables a more comprehensive, context-aware assessment process that supports strategic decision-making in IoT business environments by integrating these two approaches. In addition to highlighting the most important elements, this two-layer viewpoint clarifies the circumstances under which particular signs become crucial. In this way, the model bridges the gap between technical feasibility and business relevance, providing a scalable and adaptable decision support tool that enhances business outcomes. Unlike previous studies that have frequently concentrated on assessing the Internet of Things (IoT) within specific domains, this study presents a comprehensive framework suitable for the strategic and operational needs of enterprises pursuing sustainable digital transformation. Therefore, the methodological contribution lies not only in the combination of techniques but in their targeted and synergistic application to an under-researched context of high-impact decision-making.

The current study is positioned as a development of a decision support framework, based on expert consensus in real business contexts. Case studies can further enhance empirical validation. This provides a strong foundation for future work, where the framework can be tested and refined through the implementation of specific cases.

5. Conclusions

The development and implementation of the Internet of Things (IoT) concept are key elements of digital transformation in the modern business environment. By connecting devices, systems, and users, IoT creates new opportunities for improving efficiency and improving the quality of services, as well as for making decisions based on real-time data analysis. However, despite the great potential, numerous challenges still limit the full exploitation of IoT technologies, particularly in the domains of security, user trust, and understanding of system complexity by end users and decision makers. To enhance efficiency in sustainable IoT enterprises, this study developed and presented a multi-criteria decision support model that integrates the PFAHP and IGAHP methods. Combining these approaches enables comprehensive modeling of critical indicators while simultaneously accounting for uncertainty (through fuzzy logic) and incomplete data definition (through grey logic), resulting in a more flexible and reliable assessment model. The investigation's findings indicate that, when it comes to ranking the elements that affect the successful deployment of IoT devices, metrics such as security, value, and connectivity occupy a prominent place. However, even though they are important, qualities such as intelligence and telepresence have a lesser effect. At the same time, the application of both methodological perspectives (PFAHP and IGAHP) enabled the identification of additional, highly relevant indicators, such as information privacy, market demand, sensor networks, data management, and authorization. Comparing the obtained rankings revealed a good degree of agreement between the different analytical frameworks, further confirming the reliability of the results and the practical applicability of the proposed model. In addition to the theoretical contribution to the field of multi-criteria decision-making under uncertainty, this study offers concrete guidelines for optimizing business processes and infrastructure in the IoT environment. The results have multiple implications, ranging from supporting managers in making informed and objective decisions to better resource allocation and prioritization of investments, and the creation of regulatory and technological policies that affirm security, data protection, and trust in digital technologies. In future research, the model can be extended by applying it to various industrial domains and improved through integration with dynamic systems for real-time risk and performance assessment, further enhancing its practical value in the context of digitally oriented, sustainable business. This integration would provide methods for assessing risk and performance in real time. The findings of this study are not purely theoretical; they are derived from applied knowledge within actual IoT-adopting enterprises, providing a foundation for reliable strategic planning in uncertain and dynamic IoT environments.

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References

- Landaluce, H.; Arjona, L.; Perallos, A.; Falcone, F.; Angulo, I.; Muralter, F. A Review of IoT Sensing Applications and Challenges Using RFID and Wireless Sensor Networks. *Sensors* **2020**, *20*, 2495. [\[CrossRef\]](#)
- Chopra, K.; Gupta, K.; Lambora, A. Future Internet: The Internet of Things—A Literature Review. In Proceedings of the International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), Faridabad, India, 14–16 February 2019; pp. 135–139.
- Rosário, A.T.; Raimundo, R.J. The Integration of AI and IoT in Marketing: A Systematic Literature Review. *Electronics* **2025**, *14*, 1854. [\[CrossRef\]](#)
- Ziatdinov, R.; Atteraya, M.S.; Nabiye, R. The Fifth Industrial Revolution as a Transformative Step towards Society 5.0. *Societies* **2024**, *14*, 19. [\[CrossRef\]](#)
- Ahmad, W.; Rasool, A.; Javed; Baker, A.R.T.; Jalil, Z. Cyber Security in IoT-Based Cloud Computing: A Comprehensive Survey. *Electronics* **2022**, *11*, 16. [\[CrossRef\]](#)
- Majid, M.; Habib, S.; Javed, A.R.; Rizwan, M.; Srivastava, G.; Gadekallu, T.R.; Lin, J.C.-W. Applications of Wireless Sensor Networks and Internet of Things Frameworks in the Industry Revolution 4.0: A Systematic Literature Review. *Sensors* **2022**, *22*, 2087. [\[CrossRef\]](#)
- Ng, I.C.L.; Wakenshaw, S.Y.L. The Internet-of-Things: Review and research directions. *Int. J. Res. Mark.* **2017**, *34*, 3–21. [\[CrossRef\]](#)
- Abdel-Basset, M.; Manogaran, G.; Mohamed, M.; Rushdy, E. Internet of things in smart education environment: Supportive framework in the decision-making process. *Concurr. Comput. Pract. Exp.* **2019**, *31*, 1–12. [\[CrossRef\]](#)
- Demir, G. Strategic Assessment of IoT Technologies in Healthcare: Grey MCDM Approach. *Spectr. Decis. Mak. Appl.* **2025**, *2*, 376–389. [\[CrossRef\]](#)
- Sallam, K.; Mohamed, M.; Wagdy, M.A. Internet of Things (IoT) in Supply Chain Management: Challenges, Opportunities, and Best Practices. *Sustain. Mach. Intell. J.* **2023**, *2*, 1–32. [\[CrossRef\]](#)
- Althoe, F.; Waqar, A.; Alsulamy, S.H.; Khan, A.M.; Alshehri, A.; Falqi, I.I.; Abuhussain, M.; Abuhussain, M.A. Influence of IoT implementation on Resource management in construction. *Heliyon* **2024**, *10*, e32193. [\[CrossRef\]](#)
- Sachin, K. *Supply Chain Management Concepts and Cases Supply Chain Management Concepts and Cases*; San International Scientific Publications: Kanyakumari, India, 2024. [\[CrossRef\]](#)
- Long, M.; Schafrik, S.; Kolapo, P.; Agioutantis, Z.; Sottile, J. Equipment and Operations Automation in Mining: A Review. *Machines* **2024**, *12*, 713. [\[CrossRef\]](#)
- Cruz, C.; Tostado-Véliz, M.; Palomar, E.; Bravo, I. Pattern-driven behaviour for demand-side management: An analysis of appliance use. *Energy Build.* **2024**, *308*, 13988. [\[CrossRef\]](#)
- Choi, S.K.; Yang, C.H.; Kwak, J. System hardening and security monitoring for IoT devices to mitigate IoT security vulnerabilities and threats. *KSII Trans. Internet Inf. Syst.* **2018**, *12*, 906–918.
- Jin, J.; Gubbi, J.; Marusic, S.; Palaniswami, M. An information framework for creating a smart city through internet of things. *IEEE Internet Things J.* **2014**, *1*, 112–121. [\[CrossRef\]](#)
- Khan, M.A.; Salah, K. IoT security: Review, blockchain solutions, and open challenges. *Future Gener. Comput. Syst.* **2018**, *82*, 395–411. [\[CrossRef\]](#)
- Ly, P.T.M.; Lai, W.; Hsu, C.; Shih, F. Fuzzy AHP analysis of Internet of Things (IoT) in enterprises. *Technol. Forecast. Soc. Change* **2018**, *136*, 1–13. [\[CrossRef\]](#)
- Haseeb, K.; Bakar, K.A.; Abdullah, A.H.; Darwish, T. Adaptive energy aware cluster-based routing protocol for wireless sensor networks. *Wirel. Netw.* **2017**, *23*, 1953–1966. [\[CrossRef\]](#)
- Chang, Y.; Dong, X.; Sun, W. Influence of characteristics of the Internet of Things on consumer purchase intention. *Soc. Behav. Personal. Int. J.* **2014**, *42*, 321–330. [\[CrossRef\]](#)
- Choi, Y.-J.; Kang, H.-J.; Lee, I.-G. Scalable and Secure Internet of Things Connectivity. *Electronics* **2019**, *8*, 752. [\[CrossRef\]](#)
- Oughtona, E.; Frias, Z.; Russell, T.; Sicker, D.; Cleavelly, D.D. Towards 5G: Scenariobased assessment of the future supply and demand for mobile telecommunications infrastructure. *Technol. Forecast. Soc. Change* **2018**, *133*, 141–155. [\[CrossRef\]](#)
- Balaji, M.S.; Roy, S.K. Value Co-Creation with Internet of Things Technology in the Retail Industry. *J. Mark. Manag.* **2017**, *33*, 7–31. [\[CrossRef\]](#)
- Nabeeh, N.A.; Abdel-Basset, M.; El-Ghareeb, H.A.; Aboelfetouh, A. Neutrosophic Multi-Criteria Decision Making Approach for IoT-Based Enterprises. *IEEE Access* **2019**, *7*, 59559–59574. [\[CrossRef\]](#)
- Mohamed, I.A.; Aissa, A.B.; Hussein, L.F. Classification for IoT Threats Based on the Analytic Hierarchy Process. *Int. J. Sci. Technol. Res.* **2020**, *9*, 4860–4867.

26. Lee, I.; Lee, K. The Internet of Things (IoT): Applications, investments, and challenges for enterprises. *Bus. Horiz.* **2015**, *58*, 431–440. [\[CrossRef\]](#)
27. Alaba, F.A.; Othman, M.; Hashem, I.A.T.; Alotaibi, F. Internet of Things security: A survey. *J. Netw. Comput. Appl.* **2017**, *88*, 10–28. [\[CrossRef\]](#)
28. Volynets, V.; Popov, A.; Pushkar, T.; Frolov, M.; Babarytskyi, O. Legal Aspects of Using the Internet of Things (IOT) in Electronic Commerce. *J. Lifestyle SDGs Rev.* **2024**, *5*, e03657. [\[CrossRef\]](#)
29. Yu, J.; Bang, H.C.; Lee, H.; Lee, Y.S. Adaptive Internet of Things and Web of Things convergence platform for Internet of reality services. *J. Supercomput.* **2016**, *72*, 84–102. [\[CrossRef\]](#)
30. Lee, I. Internet of Things (IoT) Cybersecurity: Literature Review and IoT Cyber Risk Management. *Future Internet* **2020**, *12*, 157. [\[CrossRef\]](#)
31. Bekkali, A.; Essaaidi, M.; Boulmalf, M.; Majdoubi, D. Systematic Literature Review of Internet of Things (IoT) Security. *Adv. Dyn. Syst. Appl.* **2021**, *16*, 1671–1692.
32. Ulybyshev, D.; Rogers, M.; Kholodilo, V.; Northern, B. End-to-End Database Software Security. *Software* **2023**, *2*, 163–176. [\[CrossRef\]](#)
33. Taherdoost, H. Security and Internet of Things: Benefits, Challenges, and Future Perspectives. *Electronics* **2023**, *12*, 1901. [\[CrossRef\]](#)
34. Wu, J.; Chen, J.; Dou, W. The Internet of Things and interaction style: The effect of smart interaction on brand attachment. *J. Mark. Manag.* **2017**, *33*, 61–75. [\[CrossRef\]](#)
35. Stavropoulos, G.; Violos, J.; Tsanakas, S.; Leivadeas, A. Enabling Artificial Intelligent Virtual Sensors in an IoT Environment. *Sensors* **2023**, *23*, 1328. [\[CrossRef\]](#)
36. Tarifa-Fernández, J.; Sánchez-Pérez, A.M.; Cruz-Rambla, S. Internet of Things and Their Coming Perspectives: A Real Options Approach. *Sustainability* **2019**, *11*, 3178. [\[CrossRef\]](#)
37. Hoffman, D.L.; Novak, T. Emergent Experience and the Connected Consumer in the Smart Home Assemblage and the Internet of Things. *SSRN Electron. J.* **2015**. [\[CrossRef\]](#)
38. Raposo, D.; Rodrigues, A.; Silva, J.S.; Boavida, F. A Taxonomy of Faults for Wireless Sensor Networks. *J. Netw. Syst. Manag.* **2017**, *25*, 591–611. [\[CrossRef\]](#)
39. Sicari, S.; Cappiello, C.; De Pellegrini, F.; Miorandi, D.; Coen-Porisini, A. A security-and quality-aware system architecture for Internet of Things. *Inf. Syst. Front.* **2014**, *18*, 665–677. [\[CrossRef\]](#)
40. Lima, Z.; García-Vázquez, H.; Rodríguez, R.; Khemchandani, S.L.; Dualibe, F.; Del Pino, J. A System for Controlling and Monitoring IoT Applications. *Appl. Syst. Innov.* **2018**, *1*, 26. [\[CrossRef\]](#)
41. Dijkman, R.M.; Sprenkels, B.; Peeters, T.; Janssen, A. Business models for the Internet of Things. *Int. J. Inf. Manag.* **2015**, *35*, 672–678. [\[CrossRef\]](#)
42. Hakim, I.M.; Singgih, M.L.; Gunarta, I.K. Critical Success Factors for Internet of Things (IoT) Implementation in Automotive Companies, Indonesia. *Sustainability* **2023**, *15*, 2909. [\[CrossRef\]](#)
43. Lopez, C.A.; Castillo, L.F.; Corchado, J.M. Discovering the Value Creation System in IoT Ecosystems. *Sensors* **2021**, *21*, 328. [\[CrossRef\]](#)
44. Yuan, G.; Liu, Z.; Wang, Y.; Pu, D. Market Demand Optimization Model Based on Information Perception Control. *Mathematics* **2023**, *11*, 783. [\[CrossRef\]](#)
45. Maksimović, S.; Dimić, V. Multi-criteria analysis of ICT implementation in investment projects: Case Study of construction companies in the Republic of Serbia. *MB Univ. Int. Rev.* **2023**, *1*, 57–67.
46. Hsu, C.L.; Lin, C.C. An empirical examination of consumer adoption of internet of things services: Network externalities and concern for information privacy perspectives. *Comput. Hum. Behav.* **2016**, *62*, 516–527. [\[CrossRef\]](#)
47. Micheletto, M.; Zabala, P.; Ochoa, S.F.; Meseguer, R.; Santos, R. Determining Real-Time Communication Feasibility in IoT Systems Supported by LoRaWAN. *Sensors* **2023**, *23*, 4281. [\[CrossRef\]](#) [\[PubMed\]](#)
48. Patel, K.K.; Patel, S.M. Internet of Things-IOT: Definition, Characteristics, Architecture, Enabling Technologies, Application & Future Challenges. *Int. J. Eng. Sci. Comput.* **2016**, *6*, 6122–6131.
49. Singh, S.P.; Solanki, A.; Singh, T.; Tayal, A. Internet of Intelligent Things: Injection of Intelligence into IoT Devices. In *Artificial Intelligence to Solve Pervasive Internet of Things Issues*; Academic Press: Cambridge, MA, USA, 2021; pp. 85–102.
50. Chofreh, A.G.; Goni, F.A.; Klemeš, J.J. Sustainable enterprise resource planning systems implementation: A framework development. *J. Clean. Prod.* **2018**, *198*, 1345–1354. [\[CrossRef\]](#)
51. Zadeh, L.A. Fuzzy sets. *Inf. Control* **1965**, *8*, 338–353. [\[CrossRef\]](#)
52. Zadeh, L.A. The concept of a linguistic variable and its application to approximate reasoning—I. *Inf. Sci.* **1975**, *8*, 199–249. [\[CrossRef\]](#)
53. Milošević, M.R.; Milošević, D.M.; Stević, D.M.; Stanojević, A.D. Smart City: Modeling Key Indicators in Serbia Using IT2FS. *Sustainability* **2019**, *11*, 3536. [\[CrossRef\]](#)
54. Atanassov, K.T. Intuitionistic fuzzy sets. *Fuzzy Sets Syst.* **1986**, *20*, 87–96. [\[CrossRef\]](#)

55. Atanassov, K.T. Other extensions of intuitionistic fuzzy sets. *Intuitionistic Fuzzy Sets* **1999**, *35*, 179–198.
56. Yager, R.R. Pythagorean fuzzy subsets. In Proceedings of the 2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), Edmonton, AB, Canada, 24–28 June 2013; pp. 57–61.
57. Peng, X.; Yang, Y. Some results for Pythagorean fuzzy sets. *Int. J. Intell. Syst.* **2015**, *30*, 1133–1160. [\[CrossRef\]](#)
58. Karasan, A.; Ilbahar, E.; Cebi, S.; Kahraman, C. A new risk assessment approach: Safety and Critical Effect Analysis (SCEA) and its extension with Pythagorean fuzzy sets. *Saf. Sci.* **2018**, *108*, 173–187. [\[CrossRef\]](#)
59. Zulqarnain, R.M.; Xin, X.L.; Siddique, I.; Asghar Khan, W.; Yousif, M.A. TOPSIS Method Based on Correlation Coefficient under Pythagorean Fuzzy Soft Environment and Its Application towards Green Supply Chain Management. *Sustainability* **2021**, *13*, 1642. [\[CrossRef\]](#)
60. Zhang, X.; Xu, Z. Extension of TOPSIS to multiple criteria decision making with Pythagorean fuzzy sets. *Int. J. Intell. Syst.* **2014**, *29*, 1061–1078. [\[CrossRef\]](#)
61. Kahraman, C.; Oztaysi, B.; Onar, S.C. Multicriteria Scoring Methods Using Pythagorean Fuzzy Sets. In *Advances in Fuzzy Logic and Technology*; Kacprzyk, J., Szmidt, E., Zadrożny, S., Atanassov, K.T., Krawczak, M., Eds.; Springer: Cham, Switzerland, 2017; Volume 2, pp. 328–335.
62. Karasan, A.; Ilbahar, E.; Kahraman, C. A novel pythagorean fuzzy AHP and its application to landfill site selection problem. *Soft Comput.* **2019**, *23*, 10953–10968. [\[CrossRef\]](#)
63. Milošević, M.R.; Milošević, D.M.; Stević, D.M.; Kovačević, M. Interval Valued Pythagorean Fuzzy AHP Integrated Model in a Smartness Assessment Framework of Buildings. *Axioms* **2023**, *12*, 286. [\[CrossRef\]](#)
64. Haktanir, E.; Kahraman, C. A novel interval-valued Pythagorean fuzzy QFD method and its application to solar photovoltaic technology development. *Comput. Ind. Eng.* **2019**, *132*, 361–372. [\[CrossRef\]](#)
65. Onar, S.C.; Oztaysi, B.; Kahraman, C. Multicriteria Evaluation of Cloud Service Providers Using Pythagorean Fuzzy TOPSIS. *J. Mult. Valued Log. Soft Comput.* **2018**, *30*, 263–283.
66. Oztaysi, B.; Cevik, S.; Kahraman, C. Prioritization of the requirements for collaborative feedback platform for course contents using Pythagorean fuzzy sets. *World Sci. Proc. Ser. Comput. Eng. Inf. Sci.* **2018**, *11*, 1099–1106.
67. Oztaysi, B.; Onar, S.C.; Kahraman, C. Waste Disposal Location Selection by Using Pythagorean Fuzzy REGIME Method. *J. Intell. Fuzzy Syst.* **2021**, *42*, 401–410. [\[CrossRef\]](#)
68. Milošević, M.; Milošević, A.; Milošević, D.; Stanojević, A.; Dimić, V. Multicriteria Analysis of Contemporary Materials for Energy-Efficient Buildings. In Proceedings of the SFERA2016, Mostar, Bosnia and Herzegovina, 2 October 2016; pp. 46–51.
69. Selimi, A.; Milošević, M.; Saračević, M. AHP—TOPSIS Model as a Mathematical Support in the Selection of Project from Aspect of Mobility—Case Study. *J. Appl. Math. Comput.* **2018**, *2*, 257–265.
70. Milošević, D.; Milošević, M.; Simjanović, D. A Comparative Study of FAHP with Type-1 and Interval Type-2 Fuzzy Sets for ICT Implementation in Smart Cities. In *Intelligent and Fuzzy Techniques for Emerging Conditions and Digital Transformation*; Kahraman, C., Cebi, S., Cevik Onar, S., Oztaysi, B., Tolga, A.C., Sari, I.U., Eds.; INFUS 2021. Lecture Notes in Networks and Systems; Springer: Cham, Switzerland, 2022; Volume 308, pp. 845–852.
71. Ashraf, A.; Ullah, K.; Božanić, D.; Hussain, A.; Wang, H.; Puška, A. An Approach for the Assessment of Multi-National Companies Using a Multi-Attribute Decision Making Process Based on Interval Valued Spherical Fuzzy Maclaurin Symmetric Mean Operators. *Axioms* **2023**, *12*, 4. [\[CrossRef\]](#)
72. Baradaran, V. Assessment and Prioritizing the Risks of Urban Rail Transportation by Using Grey Analytical Hierarchy Process (GAHP). *J. Transp Eng.* **2017**, *4*, 255–273.
73. Stanujkić, D.; Karabašević, D.; Popović, G.; Stanimirović, P.S.; Saračević, M.; Smarandache, F.; Katsikis, V.N.; Ulutaş, A. A New Grey Approach for Using SWARA and PIPRECIA Methods in a Group Decision-Making Environment. *Mathematics* **2021**, *9*, 1554. [\[CrossRef\]](#)
74. Petković, M.S.; Milošević, D.M. On a new family of simultaneous methods with corrections for the inclusion of polynomial zeros. *Int. J. Comput. Math.* **2006**, *83*, 299–317. [\[CrossRef\]](#)
75. Petković, M.S.; Milošević, D. Improved Halley-like methods for the inclusion of polynomial zeros. *Appl. Math. Comput.* **2005**, *169*, 417–436. [\[CrossRef\]](#)
76. Ghorbanzadeh, O.; Moslem, S.; Blaschke, T.; Duleba, S. Sustainable Urban Transport Planning Considering Different Stakeholder Groups by an Interval-AHP Decision Support Model. *Sustainability* **2019**, *11*, 9. [\[CrossRef\]](#)
77. Liu, F. Acceptable consistency analysis of interval reciprocal comparison matrices. *Fuzzy Sets and Syst.* **2009**, *160*, 2686–2700. [\[CrossRef\]](#)
78. Duleba, S.; Çelikkilek, Y.; Moslem, S.; Esztergár-Kiss, D. Application of grey analytic hierarchy process to estimate mode choice alternatives: A case study from Budapest. *Transp. Res. Interdiscip. Perspect.* **2022**, *13*, 100560. [\[CrossRef\]](#)
79. Milošević, M.R.; Milošević, D.M.; Stanojević, A.D.; Stević, D.M.; Simjanović, D.J. Fuzzy and Interval AHP Approaches in Sustainable Management for the Architectural Heritage in Smart Cities. *Mathematics* **2021**, *9*, 304. [\[CrossRef\]](#)

80. Milošević, M.R.; Milošević, D.M.; Stanojević, A.D. Managing Cultural Built Heritage in Smart Cities Using Fuzzy and Interval Multi-criteria Decision Making. In *Intelligent and Fuzzy Techniques: Smart and Innovative Solutions*; Kahraman, C., Cevik Onar, S., Oztaysi, B., Sari, I., Cebi, S., Tolga, A., Eds.; INFUS 2020, Advances in Intelligent Systems and Computing; Springer: Cham, Switzerland, 2021; Volume 1197, pp. 599–607.
81. Ceballos, B.; Lamata, M.T.; Pelta, D.A. A comparative analysis of multi-criteria decision-making methods. *Prog. Artif. Intell.* **2016**, *5*, 315–322. [[CrossRef](#)]
82. Sałabun, W.; Urbaniak, K. A New Coefficient of Rankings Similarity in Decision-Making Problems. In Proceedings of the International Conference on Computational Science, Amsterdam, The Netherlands, 3–5 June 2020; Springer: Cham, Switzerland, 2020.
83. Bazigu, A.; Johnson, M. A Framework for IoT-Enabled Smart Manufacturing for Energy and Resource Optimization. *arXiv* **2025**, arXiv:2502.03040.
84. Hanifi, S.; Alkali, B.; Lindsay, G.; McGlinchey, D. Optimizing Energy and Air Consumption in Smart Manufacturing: An Industrial Internet of Things-Based Monitoring and Efficiency Enhancement Solution. *Appl. Sci.* **2025**, *15*, 3222. [[CrossRef](#)]
85. Fukuzawa, M.; Sugie, R.; Park, Y.; Shi, J. An Exploratory Case Study on the Metrics and Performance of IoT Investment in Japanese Manufacturing Firms. *Sustainability* **2022**, *14*, 2708. [[CrossRef](#)]
86. Ivanov, D.; Dolgui, A.; Panetto, H. IoT-Based Monitoring in CNC Turning Process. In *Advances in Manufacturing IV*; Springer: Cham, Switzerland, 2024; pp. 160–171.

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