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Assessing Dimensions Influencing IoT Implementation Readiness in Industries: A Fuzzy DEMATEL and Fuzzy AHP Analysis

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ABSTRACT

The rapid growth of the information age and digital technologies has ushered in innovative concepts such as Industry 4.0, smart health, digital services, and smart cities. The Internet of Things (IoT) technology has emerged as a crucial driver across domains, engaging businesses, platforms, and industries. The IoT encompasses a holistic ecosystem and a value chain that necessitate evaluating influential dimensions for successful implementation. This research applies Fuzzy DEMATEL and Fuzzy AHP methods to rank and examine dimensions affecting IoT implementation readiness. Findings underscore the significance of organizational factors, hard infrastructures, and soft infrastructures as critical dimensions. Attention to strengthening organizational aspects and developing reliable infrastructures facilitates successful IoT integration. Additionally, while relatively less significant, environmental factors, security and privacy, data analytics, and customer and training dimensions contribute to industry readiness. The combined results provide insights for decision-makers and stakeholders involved in IoT implementation, guiding the development of appropriate strategies, resource allocation, and enhancing operational efficiency. By comprehending the interrelationships and prioritizing influential factors, industries can effectively prepare for successful IoT implementation.

1. Introduction

IoT is a sustainable development trend today. The term IoT was first coined in 1999 by Kevin Ashton to monitor the supply chain and logistics processes at Procter & Gamble [1], [2]. Different groups and forums have provided various definitions and predictions about the process of IoT development and its impacts [3]. For example, the Internet community (ISOC) estimates this apprize to be 100 billion connected devices by 2025 [4]. International Telecommunication Union (ITU)

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interprets IoT as a smart environment where embedded communication modules on devices and things are connected to a wired or wireless network, enabling the exchange of information and communication between people and things [5]. Cisco, by definition, has extended IoT to the Internet of Every Thing "IoE," which includes people, places, and things [6]. The IoT consists of three perspectives, which include "object/ things oriented," "internet oriented," and "semantic oriented." Object-oriented refers to the objects and devices in the IoT that are connected by sensors. Internet-oriented refers to the smartness of the objects connected to the network that interact with each other by communication protocols. Semantic-oriented refers to the processing and analysis of data and information in a useful and meaningful way [7], [8]. The IoT ecosystem includes multiple actors and stakeholders that refers to the Internet, cloud computing, software, applications, communications networks, security and privacy mechanisms, data management and analysis, heterogeneous device and things, and other systems [9], [10]. That this ecosystem has been affected by other tangible and intangible factors or systems such as cultural-social factors [11], [12], technological infrastructure and communication networks [11], [13]–[15], policies adopted for IoT implementation, and organizational factors [7], [13], [16]–[18], etc. Organizations and businesses need to pay attention to the IoT value chain that connects these systems and forms the foundation of IoT [5]. The IoT applications can be mentioned in areas such as the environment, transportation and logistics, retail, smart services, smart city and home, manufacturing industries, healthcare, and more [7], [14], [19], [20].

Countries, Industries, businesses, and organizations are seeking to assess the readiness of their different levels to implement IoT and to find the challenges and factors effective on it. Most of these documents have examined the challenges, factors, and indicators effective on IoT implementation. Still, they need to evaluate a coherent model for assessing the readiness of IoT with specific dimensions. As mentioned, the IoT ecosystem has multiple actors in which technologies play a special role in it [1], [2], [10], but these technologies and actors need a value chain to connect them to shape the IoT's building; On the other hand, this value chain has been created through other tangible and intangible factors, especially suppliers and service providers, which requires collaboration at the chain level [5], [21]. This value chain "or in general the factors or dimensions involved in this chain" may shape the development of IoT and understanding and evaluation by organizations and businesses to facilitate IoT deployment. But on the other hand, this value chain can also vary in each business depending on the type and level of assessment of readiness to implement IoT [5], [17]. For this reason, this article seeks to answer the question of what are the most important dimensions of IoT readiness. And which of these dimensions has the highest priority over the other and plays the most role in the proposed model?

Today, most industries and businesses are aware of the benefits of IoT and are seeking to incorporate it into their infrastructure. However, the use of IoT necessitates careful consideration of the actors involved in its ecosystem and the challenges that lie ahead. Before implementing IoT, it is essential to assess the factors that impact this ecosystem, particularly the availability of both soft and hard infrastructures, a concept known as readiness. According to Parasuraman (2000), technology readiness encompasses four principles that reflect how individuals and users respond to the preparedness for new technology or innovation, highlighting the softer aspects of readiness, such as trust, response mode, and attitude [22]. Recognition and evaluation of these dimensions and principles can facilitate the readiness and adoption of technology implementation. However, this is just one aspect of IoT readiness that can be helpful, and other factors and dimensions must also be considered. Therefore, IoT readiness needs to be examined within a broader context or framework, encompassing the various dimensions and factors that influence it. The intensity and impact of these dimensions and factors can vary across different businesses and countries. By properly analyzing the factors affecting the IoT ecosystem and identifying the dimensions that represent these influential factors while providing the necessary infrastructure, the benefits and potential of IoT can be fully realized.

Assessing this readiness becomes a critical step and solution for implementing new technologies like IoT, particularly in industries. This research aims to identify the important dimensions affecting IoT implementation readiness in industries and assess the relationship between the dimensions. Furthermore, the study seeks to address the following questions:

- What are the factors and enablers that affect IoT readiness?
- How are these dimensions prioritized in terms of importance?
- What causal relationship exists between these dimensions?

Since these dimensions and their associated indicators in the IoT value chain are closely intertwined, it is difficult to determine the relative importance of one over the other. The significance of each dimension depends on the preferences and strategies of the developer and business implementing IoT solutions. Given the existence of causal and effect relationships among these dimensions, it becomes necessary to evaluate them based on expert opinions. However, it's important to acknowledge that expert opinions inherently involve a certain degree of judgment and uncertainty. Typically, experts do not provide explicit responses or definitive answers; instead, they tend to express their views using qualitative terms such as 'low,' 'high,' and 'medium.' To tackle such situations characterized by uncertainty, Fuzzy set theory emerges as a powerful mathematical tool. In this study, the problem is addressed using the "Fuzzy logic" method, which involves modeling the experts' opinions as Fuzzy numbers and employing the Fuzzy DEMATEL method to analyze the causal relationships between dimensions and also prioritization the dimensions with Fuzzy AHP. These approaches allow for ranking the dimensions and discussing their relative importance.

Given the above, this research includes the following sections: Section 2 outlines the research methodology and the main concepts of Fuzzy logic theory and the DEMATEL method. Section 3 reviews the problem details and the method of solving it. Then the findings of prioritizing the dimensions of IoT readiness using the Fuzzy DEMATEL method are expressed, and the validity of the proposed model is obtained. In Section 3, the problem details and the method of solving it are reviewed, and then the findings of prioritizing the dimensions of IoT readiness using the Fuzzy DEMATEL method are expressed, and the validity of the proposed model is obtained; finally, section 4 is Addressing conclusions and summarizing.

1.1 Literature Review

As mentioned in Section 1, IoT operates within an ecosystem where its different elements and subsystems interact and collaborate. The IoT value chain plays a crucial role in shaping this ecosystem, as it involves various actors and stakeholders working together to ensure seamless connectivity. Numerous studies have delved into the IoT ecosystem, identifying the components that demonstrate convergence among them. Additionally, these studies have examined the factors that influence the IoT ecosystem, including drivers, enablers, dimensions, indicators, challenges, and solutions that have a significant impact on the implementation and deployment of IoT. These factors are interconnected within the IoT value chain and have implications for the readiness of the banking sector to embrace IoT.

Industries and businesses need to address IoT-enabled technologies by collaborating and integrating with their ecosystem. These technologies encompass various computing paradigms, such as cloud, fog, and edge, which facilitate the transfer and management of data from devices to data centers [23]. They also involve Big Data analytics technologies and algorithms for processing large volumes of data [9], [24]. Additionally, Artificial Intelligence tools play a crucial role in extracting and analyzing valuable data and enhancing data and information security on gateways and networks [25], [26]. Semantic technologies, such as the Web of Things (WoT), enable data display to end-users on web pages and facilitate device monitoring and data management at the source [27]. Research has been conducted to explore these technologies further. For example, Wang *et al.* [18] presented a model that considers three IoT-related technologies essential for industries' readiness in implementing IoT: the Internet of Everything (IoE), which encompasses protocols for communication and connectivity among IoT devices; a cloud of things (CoT), which provides cloud platforms for data collection and analysis using various analytical tools; and the web of things (WoT), which focuses on displaying and configuring objects and their statuses through web-based interfaces. Security and privacy challenges also pose significant concerns for industries adopting these technologies [18]. In another study, Albishi & *et al.* [2] explored the IoT ecosystem and identified emerging technologies, including cloud computing, semantic technologies, autonomy, and awareness, as key challenges and benefits for businesses in the future. Also, the International Telecommunication Union (ITU) [61] has examined four closely related technologies in ICT, including IoT, big data, cloud computing, and artificial intelligence. They highlighted the potential for sustainable development and business collaboration through the analytics of data generated from these connections. The use of these technologies requires the availability of appropriate infrastructure, services, and skills, therefore has offered four complementary factors for implementation and understanding these technologies, in particular, IoT: 1) access appropriate physical infrastructure, including devices, networks, data storage, and processing; 2) essential services such as connections, computing services, and data transmission channels; 3) user knowledge and skills; 4) adoption Policies to develop sustainable and scalable solutions [13].

Saarikko *et al.* [1] identified several factors that affect the IoT ecosystem, such as technical infrastructure, communication networks, connectivity and communication between objects and devices, data management, and involvement of various IoT actors. They emphasized the importance of businesses understanding the IoT value chain and designing their business models accordingly. Furthermore, they highlighted the need to ensure that customers have a good understanding of IoT-based products and services and to offer appropriate recommendations based on this understanding. Kshetri [28] discussed the factors that influence the implementation of IoT, categorizing them into supply-side, demand-side, and institutional factors. These factors encompass various challenges, including the role of suppliers and internal and external collaboration between companies, involvement of startups and mobile operators, and more. Zaidi [8] examined Malaysia's readiness for implementing IoT, considering factors such as the development of communication and network infrastructure, management systems, strategies and planning at both micro and macro levels, availability of skills and experts, data and information management, and security and privacy mechanisms. The study emphasized the significant role played by both ICT and non-ICT factors in IoT implementation. Asir *et al.* [7] highlighted the challenges, particularly related to physical and social infrastructure, faced during IoT implementation in India. These challenges encompassed factors like communication and network infrastructure, energy capacity, investment from public and private enterprises, government's involvement and participation, and competition among service providers. Mukayisenga *et al.* [15] conducted an analysis of IoT indicators based on stakeholder perspectives in Rwanda. The study focused on economic and social dimensions, as well as policy and technological challenges. Key factors identified included ICT-related infrastructure, data and information management and analysis, human capacity in terms of skills and experts, security and privacy mechanisms, electronics ownership, government policies, and the level of understanding and adoption of IoT among individuals and organizations. Branco *et al.* [17] employed a two-dimensional approach, assessing industry 4.0 readiness by evaluating digital infrastructure (ICT) and the ability to analyze and handle big data. The first dimension encompassed hardware and devices, as well as the communication networks between them, while the second dimension focused on the capacity to process and utilize the information and data generated by the first dimension. The main variables considered within these dimensions were ICT infrastructure and communication networks, communication platforms and devices, skilled and experienced staff, and the role of public policymakers and resource allocation. Schumacher *et al.* [29] presented a maturity model for assessing industry 4.0 readiness and maturity in manufacturing organizations. Their model consisted of 62 items distributed across nine dimensions: strategy, leadership, customers, products, operations, culture, individuals, governance, and technology. The assessment results indicated that the goals of the model could be adjusted based on a company's self-evaluation results and strategic actions, highlighting the unique impact of each dimension on an organization. Sheen and Yang [30] explored the technical, organizational, and cultural factors that influence a company's readiness to embrace innovation and intelligent manufacturing. These factors included having appropriate hardware, software, and network conditions in the factory (ICT infrastructure), systems integration, remote control capabilities, flexibility, strategic planning, human resources, and fostering an innovative culture within the enterprise. Anggrahini *et al.* [31] utilized Schumacher's industry 4.0 readiness model to assess the readiness of the intelligent production system in the tuna processing industry. In addition to the nine dimensions proposed by Schumacher, they introduced the development team's dimension, which focused on system development and maintenance, as well as expediting organizational transformation and procedures. Table 1 presents the frequency distribution of the 8 dimensions examined in previous research.

Table 1
The frequency distribution of the IoT implementation readiness dimensions examined in previous research

Authors	Dimensions							
	SI*	HI*	EF*	OF*	CT*	SUI*	SP*	DA*
[32]	✓	✓					✓	
[33]				✓				
[34]	✓				✓		✓	
[35]		✓			✓		✓	
[36]			✓	✓		✓	✓	
[37]	✓	✓	✓	✓	✓			
[38]			✓	✓		✓	✓	
[39]		✓	✓	✓	✓			
[40]	✓	✓	✓	✓			✓	
[41]	✓	✓	✓	✓				
[42]			✓	✓	✓	✓		
[43]		✓			✓		✓	
[44]	✓	✓					✓	✓
[45]	✓	✓		✓	✓		✓	
[46]			✓	✓	✓		✓	
[47]			✓	✓				
[48]	✓	✓	✓		✓		✓	
[17]	✓	✓	✓	✓		✓		✓
[49]			✓	✓		✓		
[18]	✓	✓					✓	

Authors	Dimensions							
	SI*	HI*	EF*	OF*	CT*	SUI*	SP*	DA*
[12]	✓	✓	✓	✓	✓	✓	✓	
[30]	✓	✓		✓		✓		
[50]	✓	✓	✓	✓	✓	✓		
[51]	✓	✓		✓			✓	✓
[52]	✓	✓						
[53]			✓	✓		✓		
[16]		✓				✓		
[31]	✓	✓	✓	✓	✓	✓		
[3]	✓	✓		✓				✓
[2]	✓	✓					✓	
[1]	✓	✓		✓	✓			
[54]				✓			✓	
[5]	✓	✓	✓	✓		✓		
[28]		✓	✓	✓	✓	✓	✓	
[13]	✓		✓	✓	✓		✓	✓
[55]	✓	✓	✓	✓	✓	✓	✓	
[8]	✓	✓		✓		✓	✓	
[56]	✓	✓						
[15]	✓		✓	✓	✓		✓	✓
[57]				✓				
[58]	✓	✓	✓	✓	✓			
[59]	✓	✓					✓	
[60]	✓	✓	✓				✓	✓
[29]	✓	✓	✓	✓	✓	✓		
[61]	✓	✓	✓			✓		
[7]		✓	✓			✓		
[10]	✓	✓					✓	
Our Study	✓	✓	✓	✓	✓	✓	✓	✓

* Soft infrastructure (SI)   * Hard infrastructure (HI)
* Environmental Factors (EF)   * Organizational Factors (OF)
* Customers and Training (CT)   * Supply Infrastructure (SUI)
* Security and Privacy (SP)   * Data Analytics (DA)

As previously mentioned, this study focuses on analyzing the affective dimensions of IoT implementation readiness in industries to prioritize and determine each dimension's importance. For this purpose, based on previous research, the proposed model for IoT readiness consists of eight dimensions, summarized in Table 2.

Table 2
Dimensions affecting IoT implementation readiness in industries

Coding	Dimensions
D1	Soft infrastructures
D2	Hard infrastructures
D3	Environmental factors
D4	Organizational factors
D5	Supply infrastructures
D6	Customers and Training
D7	Security and privacy
D8	Data analytics

There are several indicators in these dimensions. The following have come indicators for each dimension according to the documents and researches above and illustrates the descriptions of the dimension of itself:

1.1.1. Dimension of Soft Infrastructure

The soft infrastructure dimension involves software, platforms, and operating systems compatible with the IoT ecosystem. It also includes integrated databases, configuration and integration of applications, data analytics tools, and cloud networks and platforms. IoT implementation's effectiveness relies on robust and scalable software and platforms, efficient data management systems, and seamless integration of various applications and tools.

1.1.2. Dimension of Hard Infrastructure

The hard infrastructure dimension focuses on the physical and non-physical objects and devices used in the IoT ecosystem. It encompasses factors such as the speed and quality of internet access, network strength, strong servers, database and data storage infrastructures, IoT protocols and standards, and the availability of smart sensors and chips. The reliability and efficiency of IoT implementation heavily rely on the quality of hardware infrastructure, including the network, devices, and sensors used.

1.1.3. Dimension of Environmental Factors

Environmental factors refer to cultural, social, and regulatory aspects that influence IoT implementation. This dimension includes factors such as cultural norms, societal acceptance and interest in IoT, the level of digital literacy among users, government policies and regulations related to IoT, the role of stakeholders and regulators, government incentives and support, and international partnerships and cooperation. The cultural context, regulatory frameworks, and international collaborations influence the success of IoT implementation.

1.1.4. Dimension of Organizational Factors

Organizational factors encompass managerial aspects, policies and strategies, employees and experts, standards and evaluation systems, and financial considerations. Managerial factors include senior managers' support and commitment, awareness and understanding of IoT, and involvement in the implementation process. Organizational policies and strategies involve the development of comprehensive plans, the adoption of regulations and standards, and the strengthening of infrastructure. The availability of skilled employees, experts, and financial resources dedicated to IoT projects is crucial for successful implementation.

1.1.5. Dimension of Supply Infrastructures

The supply infrastructure dimension focuses on the availability of companies, organizations, and startups that provide IoT services. It includes the presence of both hard and soft infrastructures within the IoT ecosystem. Additionally, the involvement of financing agencies, collaboration among operators to set up the network, and the participation and cooperation of government agencies and institutions play significant roles in ensuring a robust supply chain for IoT implementation.

1.1.6. Dimension of Customer and Training

This dimension pertains to customer awareness and training regarding IoT-based services. It involves familiarizing customers with the benefits and functionalities of IoT, providing training courses and packages, and ensuring the affordability of IoT services. Effective customer education and training contribute to adopting and accepting IoT solutions.

1.1.7. Dimension of Security and Privacy

The security and privacy dimension focuses on safeguarding the IoT ecosystem. It includes security mechanisms such as authentication modules, access control mechanisms, and security software. Additionally, network and communication infrastructure security, unique IPs, and data integrity and accuracy are vital considerations to protect IoT systems from potential threats and breaches.

1.1.8 Dimension of Data Analytics

The data analysis dimension encompasses the acquisition, collection, processing, integration, storage, and analysis of data in the context of IoT implementation. It involves utilizing data analysis tools and algorithms, managing big data, and leveraging cloud computing for efficient processing and storage. Data analysis plays a crucial role in extracting valuable insights, optimizing operations, and making informed decisions in the IoT ecosystem.

By considering these dimensions and their respective factors, organizations and stakeholders can effectively prioritize and address the key aspects that impact the readiness for IoT implementation in industries. Understanding and addressing these dimensions will contribute to the successful deployment and utilization of IoT solutions in various industrial sectors.

2. Methodology

The following provides a brief overview of Fuzzy sets, the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) method, and the Fuzzy Decision-Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) method, along with their respective steps.

2.1. Fuzzy sets

In the real world, the goals and limitations of decision-making are not precisely known [62]; Sometimes, human judgments in decision-making are not entirely accurate and are faced with ambiguity [63]–[65]. These judgments are expressed in linguistic terms "low," "medium," "high," etc., and this unreliability and uncertainty in decision-making are related to the environment [66], [67]. The theory of Fuzzy number sets, introduced by Zadeh [60], can effectively counter ambiguities about linguistic thoughts and terms (human judgments) expressed as linguistic variables when making decisions. When information is incomplete or ambiguous, it determines its effectiveness in decision-making [68], [69]. Fuzzy numbers can be used to transform these linguistic terms into decision-making, meaning that these numbers represent the linguistic variables of experts in decision-making.

Unlike definite sets, Fuzzy sets use the rate or "degree of membership" for the membership of an element to the set [70], [71]. For any element such as X in the crisp set of A, it can be represented by the following membership function (1):

$$\mu_A(x) = \begin{cases} 1 x \in A \\ 0 x \notin A \end{cases} \quad (1)$$

Whereas in a Fuzzy set, the membership of each element in the set can be expressed as follows: $\mu_A(x) \in [0,1]$, In other words, the membership of any element, such as X in the set of A, can have some value between zero and one, Where $\mu_A(x) = 1$ indicates X belongs to A, and while $\mu_A(x) = 1$ indicates that X does not belong to the Fuzzy set of A, and this is the main step in modeling uncertainty. On the other hand, Fuzzy numbers are generalizations of crisp numbers. Triangular and trapezoidal Fuzzy numbers are the most common ones [70]–[73]. $F = (l, m, u)$ represents the triangular Fuzzy number, as shown in Figure 1 [63], Where l is the number or lower bound, m is the number mode and, u is the number or upper bound. The membership function of a triangular Fuzzy number can be defined as Eq. (2) [63], [70], [74].

$$\widetilde{M}(x) = \begin{cases} 0, x < l, \\ (x-l)/(m-l), l \le x \le m, \\ (u-x)/(u-m), m \le x \le u, \\ 0, x > u, \end{cases} \quad (2)$$

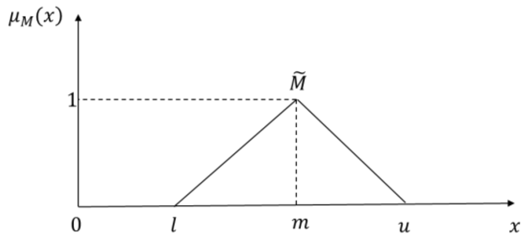

Fig. 1. Show triangular Fuzzy number [63]

For two triangular Fuzzy numbers
$\tilde{A}_1 = (l_1, m_1, u_1)$ and $\tilde{A}_2 = (l_2, m_2, u_2)$, the arithmetic operators can be defined as follows [63], [70], [75]:

1- Sum of triangular Fuzzy numbers: $\tilde{A}_1 + \tilde{A}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2)$
2- Subtraction of triangular Fuzzy numbers: $\tilde{A}_1 - \tilde{A}_2 = (l_1 - u_2, m_1 - m_2, u_1 - l_2)$
3- Multiply of triangular Fuzzy numbers: $\tilde{A}_1 \times \tilde{A}_2 = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2)$
4- Division of triangular Fuzzy numbers: $A_1 / \tilde{A}_2 = (l_1 / l_2, m_1 / m_2, u_1 / u_2)$

2.2 Fuzzy-AHP method

Despite the popularity of AHP, it is criticized due to its weakness in examining the decision-makers' perceptions and the ambiguity in their opinion [76], [77]. Fuzzy-AHP is based on Fuzzy logic that was proposed against classical logic and did not have the weaknesses of AHP. Fuzzy logic is a powerful tool and is very efficient for solving complex problems that depend on inference, decision-making, and reasoning [78]. The expert freely expresses his opinions in a range of values and can show his hesitant opinion with numbers [79]; Therefore, in this research, an attempt has been made to use the Fuzzy-AHP method to consider the uncertainty in the opinion of experts and to prioritize the factors affecting the readiness of IoT in industries by examining the uncertainty. The Fuzzy-AHP method consists of the following parts:

The First stage**, determining indicators:** With the systematic review method, factors affecting the readiness of IoT in industries were identified (Table 2).

The Second stage, **pairwise comparison matrix**: After defining the criteria, pairwise comparison is used. Pairwise comparison is obtained based on nine hourly spectra from experts [76].

The Third stage, **forming the Fuzzy fusion matrix**: Experts' opinions are combined and converted into Fuzzy triangular numbers in this fusion method. The Fuzzy triangular number consists of an interval with three members.

$$\widetilde{a_{ij}} = \left[a_{ij}, b_{ij}, c_{ij}\right] \tag{2}$$

- Minimum expert opinions (a)
- Geometric mean of experts' opinions (b)
- Maximum expert opinions (c)

The Fourth stage, **calculation of Fuzzy weight from the consolidated matrix**: The score calculation for each criterion is obtained as the geometric mean of each line.

$$Z_i = \left[\frac{a_{i1}\times a_{i2}\times a_{i3}\times ,\ldots}{n}\right] \tag{4}$$

Those divide the score of each criterion by the total score to have the nature of weight (a number between 0 and 1).

$$W_i = \frac{Z_i}{(Z_1+Z_2+Z_3+\cdots)} \tag{5}$$

The Fifth stage, **Defuzzification**: A definite number can be reached with the simple arithmetic average of the triple elements of Fuzzy numbers.

$$W_i = \frac{W_{ai}+W_{bi}+W_{ci}}{3} \tag{6}$$

The Sixth stage, **normalization**: In order for the obtained values to have the nature of weight, each of the weights is divided by the total weight to make a normalization. Finally, according to the factor of 100 in the formula, the importance of the indicators in Table 2 is obtained in terms of percentage.

$$NW_i = \frac{W_i}{\sum_{i=1}^{n} W_i} \times 100 \tag{7}$$

2.3. DEMATEL Technique

DEMATEL's method (Decision Making Trial and Evaluation Laboratory) was introduced at the Geneva Research Center between 1972 to 1976 to discuss complex and comprehensive decision-making issues by Gabus and Fontella [63], [71]. The DEMATEL method is formed based on matrix theory and graph theory (Digraph) [80], Which can evaluate cause-and-effect relationships between variables or criteria [66]. This method is a practical and effective tool for visualizing complex causal relationships. By establishing an understandable structural model of the system, the method identifies the relationships between the criteria and expresses the influence and severity of each variable [70], [80].

The Fuzzy DEMATEL method uses Fuzzy linguistic variables and analyzes the cause-and-effect relationships between variables facilitating decision-making under environmental uncertainty [66], [75]. Namely, the experts determine the severity of the impact and importance of each of the variables with verbal expressions. To avoid ambiguity, these expressions are converted to Fuzzy numbers such as, Fuzzy triangular numbers [70], [71], [80]. The Fuzzy DEMATEL method has been used in management and collaboration in the supply chain, tracking, energy supply, supplier selection, operation, learning management system, and other research areas [63], [66], [70], [71], [74], [75], [80]. This research uses triangular (or triple) Fuzzy numbers to determine the distance based on the given values (converting qualitative expressions to Fuzzy numbers) by experts' opinions.

The steps of the Fuzzy DEMATEL method are as follows [63], [66], [68], [70], [71], [74], [75], [78], [80]–[85]:

The first stage, **group formation:** At this stage, consult with experts with sufficient knowledge and experience about the issue.

The second stage is **determining the criteria to be evaluated and the design of linguistic scales**: The research or problem's dimensions and indicators are defined in this stage. The experts are asked to compare pairs of criteria based on their impact on each other, using a square matrix to measure the relationships between the criteria. Experts every home of this matrix fill using qualitative terms (linguistic) and based on pairwise comparisons. This matrix is called the "Initial Direct-Relation Matrix." After completing the matrices, verbal expressions must be converted to Fuzzy numbers. The following Table 3 and Figure 2 lists the Fuzzy equivalent of the variables used in the experts' language:

Table 3
The Linguistic Terms and their Fuzzy equivalents in the research [70], [80]

Linguistic Variables/ Verbal Terms	Crisp equivalent/ Influence score	Triangular Fuzzy Numbers
No Influence (NO)	0	(0.0, 0.1, 0.3)
Very Low Influence (VL)	1	(0.1, 0.3, 0.5)
Low Influence (L)	2	(0.3, 0.5, 0.7)
High Influence (H)	3	(0.5, 0.7, 0.9)
Very High Influence (VH)	4	(0.7, 0.9, 1.0)

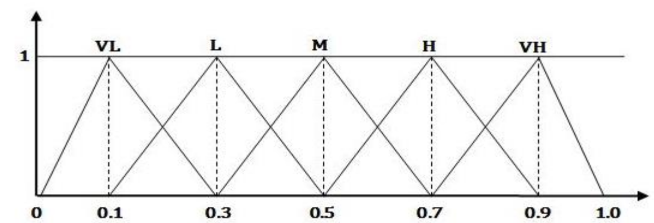

Fig. 2. Triangular Fuzzy number diagram for the selected verbal expressions in Table 3

The second step in this stage is to calculate the average matrix of experts' opinions in accordance with the following Eq. (8):

$$\tilde{z} = \frac{\tilde{x}^1+\tilde{x}^2+\tilde{x}^3+\ldots+\tilde{x}^p}{p} \tag{8}$$

In this regard, p is the number of experts, and $\tilde{x}^1$, $\tilde{x}^2$, and $\tilde{x}^p$are the paired scale 1 to p, respectively, and $\tilde{z}$ is the triangular Fuzzy number in the form of $\tilde{z}_{ij} = (l_{ij},\ m_{ij},\ u_{ij})$.

The third stage, **normalization of the Direct-Relations Matrix**: With possession "Initial Direct-Relation Matrix," the matrix of " normalized direct-relation Fuzzy" is made. At this stage, the table of averages of the resulting opinions is normalized to make its scale comparable and standard. The following Eqs. (9,10) are used to normalize:

$$\tilde{a}_{ij} = \sum_{j=1}^{n} \tilde{Z}_{ij} = \left(\sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij}\right), u = \max_{1 \le i \le n}\left(\sum_{j=1}^{n} u_{ij}\right) \tag{9}$$

$$\tilde{x} = \begin{bmatrix} \tilde{x}_{11}\tilde{x}_{12}\dots\tilde{x}_{1j} \\ \tilde{x}_{21}\tilde{x}_{22}\dots\tilde{x}_{2j} \\ \dots \\ \dots \\ \dots \\ \tilde{x}_{i1}\tilde{x}_{i2}\dots\tilde{x}_{ij} \end{bmatrix}, \tilde{x}_{ij} = \frac{\tilde{Z}_{ij}}{u} = \left(\frac{l_{ij}}{u}, \frac{m_{ij}}{u}, \frac{u_{ij}}{u}\right) \tag{10}$$

Here i is the row number, and j, the column number, for example, $\tilde{x}_{12}$ represents the degree of impact that the dimension of 1 has on the dimension of 2. And the relation $\tilde{x}_{ij}$ is used to calculate the matrix of average $\tilde{x}$.

The fourth stage is **calculating the total-relation Fuzzy matrix**: In this stage, by first calculating the inverse of the normalized matrix, then subtracting it from the identity matrix (unit), and finally multiplying the norm matrix in the resulting matrix. To do this, it first needs to compute the Fuzzy matrix of total relations through relation $\tilde{T} = \lim_{n \to \infty}(x + x^2 + \dots + x^n)$ and then obtain each Fuzzy number element that is $\tilde{t}_{ij} = (l_{ij}'', m_{ij}'', u_{ij}'')$ from the relations (11) and (12):

$$\tilde{T} = \begin{bmatrix} \widetilde{t_{11}} & \dots & \widetilde{t_{1n}} \\ \vdots & \ddots & \vdots \\ \widetilde{t_{m1}} & \dots & \widetilde{t_{mn}} \end{bmatrix} \tag{11}$$

$$[l_{ij}''] = x_l \times (I - x_l)^{-1}, \quad [m_{ij}''] = x_m \times (I - x_m)^{-1} \quad \text{and} \quad [u_{ij}''] = x_r \times (I - x_u)^{-1} \tag{12}$$

$I$is the unit matrix in these relationships, and x_l, x_m, and $x_u$are each matrix $n \times n$; Its elements form the lower, middle, and upper numbers of the Fuzzy numbers of the triangular matrix x, respectively.

The fifth stage is **creating and analyzing a causal diagram**: The first step is to calculate the sum of elements of each row (D_i) and each column (R_i) matrix of T. In order to draw a causal diagram, these two values must be stated in the form of a crisp. For this reason, the "Mean value" method is used to "defuzzification" these two values. Use the following relation (13) to defuzzification the values to get a crisp value:

$$B = \frac{l + u + 2m}{4} \tag{13}$$

The next step is to use the following relations (9) for the sum row and column:

$$\widetilde{D} = (\widetilde{D}_i)_{n \times 1} = \left[\sum_{j=1}^{n} \tilde{T}_{ij}\right]_{n \times 1} \quad \text{and} \quad \tilde{R} = (\tilde{R}_i)_{1 \times n} = \left[\sum_{j=1}^{n} \tilde{T}_{ij}\right]_{1 \times n} \tag{14}$$

Where $\tilde{D}$and $\tilde{R}$are matrices $n \times 1$ and $1 \times n$, respectively. The Importance of the criteria (dimensions)$(\tilde{D}_i + \tilde{R}_i)$ and the relationship between the criteria $(\tilde{D}_i - \tilde{R}_i)$ are determined in the next step. If $\tilde{D}_i - \tilde{R}_i > 0$ is, the relevant criterion is "effective," and if $\tilde{D}_i - \tilde{R}_i < 0$ is, the relevant criterion is " Impressive." The next step $\tilde{D}_i + \tilde{R}_i$ and $\tilde{D}_i - \tilde{R}_i$ from the previous step, should show the relationships between the criteria. After the defuzzification of the numbers, a Cartesian coordinate system is plotted. In this system, the longitudinal axis represents the values of $\tilde{D}_i + \tilde{R}_i$ and the transverse axis of the values of $\tilde{D}_i - \tilde{R}_i$. Therefore, the horizontal vector in the coordinate system is the amount of impact of the factor or dimension desired in the system; in other words, whatever this amount is greater for one factor, it interacts more with other system factors. The vertical vector of the coordinate system shows the power of influence of each factor. If this value is positive for a factor, the variable is causal; if negative, the variable is considered an effect.

3. Result

3.1. Validation of Fuzzy DEMATEL Assessments

According to the steps of the Fuzzy DEMATEL method and the first and second steps, a questionnaire was given to ten university experts working in the field of the Internet of Things; And they were asked to identify the relationships and importance between the dimensions listed in Table 2. After collecting the questionnaires, the verbal expressions were modeled as Fuzzy numbers using the relationships mentioned in Table 3. Thus, the Initial Direct-Relations Matrix was obtained. After calculating the above matrix, according to relations (9) and (10), the initial direct-relations matrix can be normalized. According to equations (11) and (12) is calculated the total-relations Fuzzy matrix. According to the fifth step and equation (13), the above matrix is defuzzification and then the sum of the elements of each row (D_i) and each column (R_i) of the matrix is calculated according to equation (14), which Table 4 shows these results.

Table 4
The Defuzzification Matrix and sum of its rows and columns

DF	D1	D2	D3	D4	D5	D6	D7	D8	D
D1	0.21	0.27	0.27	0.3	0.29	0.31	0.26	0.26	2.18
D2	0.31	0.22	0.31	0.33	0.33	0.33	0.29	0.28	2.4
D3	0.29	0.27	0.2	0.31	0.3	0.31	0.26	0.26	2.2
D4	0.28	0.27	0.26	0.22	0.29	0.29	0.26	0.26	2.12
D5	0.31	0.3	0.29	0.32	0.23	0.31	0.28	0.27	2.3
D6	0.29	0.28	0.26	0.31	0.31	0.22	0.26	0.25	2.16
D7	0.38	0.36	0.36	0.4	0.4	0.39	0.25	0.35	2.87
D8	0.32	0.31	0.31	0.35	0.35	0.34	0.3	0.21	2.5
R	2.38	2.29	2.27	2.54	2.54	2.5	2.15	2.13	

Finally, according to the results of Table 5, the importance of dimensions $(\tilde{D}_i + \tilde{R}_i)$ and the relationship between dimensions $(\tilde{D}_i - \tilde{R}_i)$ are determined. Determining the degree of Cause and Effect of the dimensions is necessary. As stated, if $(\tilde{D}_i - \tilde{R}_i)$ is positive, that dimension will be Cause, and if its value is negative, it will be Effect.

Table 5
The amount of importance and relation between dimensions (cause and effect)

Dimensions	D+R	D-R	Cause/Effect
D1	4.55	- 0.2	Effect
D2	4.68	0.11	Cause
D3	4.47	- 0.07	Effect
D4	4.66	- 0.42	Effect
D5	4.77	- 0.17	Effect
D6	4.66	- 0.33	Effect
D7	5.03	0.72	Cause
D8	4.63	0.37	Cause

Figure 3 shows the importance and Cause and Effect between dimensions. The horizontal axis indicates the importance of the dimensions, and the vertical axis indicates their cause and effect. According to the above points, the dimensions located above the horizontal axis are classified as causal dimensions (cause), and the dimensions located below the horizontal axis are classified as effect dimensions (effect). Also, higher dimensions indicate a greater degree of cause, and lower dimensions indicate a greater degree of effect. On the other hand, among the cause-effect dimensions, the value of $(\tilde{D_i} + \tilde{R_i})$ indicates the intensity of the interaction of each dimension with other dimensions. Thus, in the group of Cause dimensions, the higher the value of $(\tilde{D_i} + \tilde{R_i})$, the dimension has higher importance and priority. Also, among the Effect dimensions, the lower the value of $(\tilde{D_i} + \tilde{R_i})$, the dimension has higher importance and priority. The analysis results show that no dimension alone is the most important among the dimensions affecting the readiness of industries to implement IoT. As can be seen, "Security and Privacy," "Data analysis," and "Hard infrastructure" are among the Cause dimensions and "Environmental factors," "Supply infrastructures," "Soft infrastructure," "Customers and Training," and "Organizational factors" have been identified as Effect dimensions.

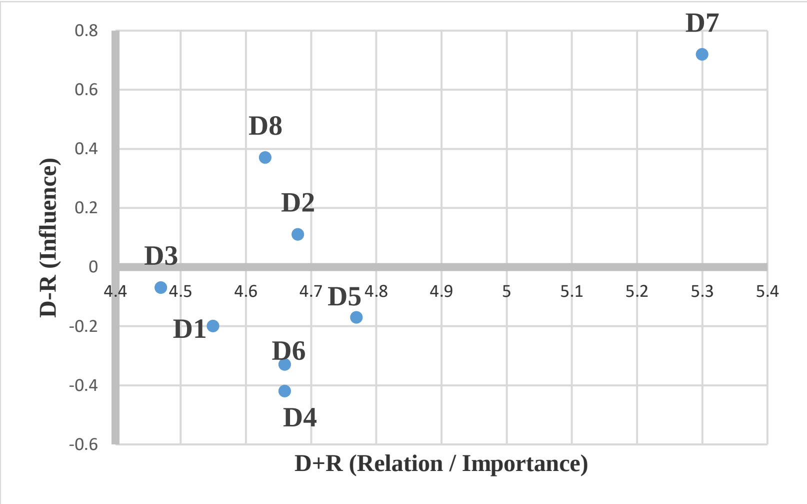

Fig. 3. The diagram of importance (D + R) and amount of cause and effect (D-R) of the dimensions of IoT readiness

According to the above points in Figure (3), the dimensions above the horizontal axis are considered causal. In contrast, the dimensions below the horizontal axis are classified as dependent or Effect. Additionally, the higher the dimensions are, the greater their degree of Cause, and the lower the dimensions are, the greater their degree of Effect. On the other hand, among the Cause-and-Effect dimensions, the value of $\left(\tilde{D}_i + \tilde{R}_i\right)$ indicates the intensity of interaction of each dimension with other dimensions. In this way, in the group of Cause dimensions, the higher the amount of $(\tilde{D}_i + \tilde{R}_i)$, the more important that dimension is, and it is a higher priority. Also, among the Effect dimensions, the lower the amount of $(\tilde{D}_i + \tilde{R}_i)$, the more important that dimension is, and it is a higher priority. The analysis results show that no dimension alone has the greatest importance among the dimensions influencing the readiness of IoT in industries. As observed, "Security and Privacy," "Data Analytics," and "Hardware Infrastructure" are among the Cause dimensions, while "Environmental Factors," "Supply Infrastructure," "Soft Infrastructure," "Customers and Training," and "Organizational Factors" are among the Effect dimensions identified. The degree of Cause-Effect of dimensions influencing the readiness of IoT in industries, in order, includes: "Security and Privacy," "Data Analytics," "Hardware Infrastructure," "Environmental Factors," "Supply and Delivery Infrastructure," "Soft Infrastructure," "Customers and Training," and "Organizational Factors." Furthermore, "Security and Privacy" is the most Cause dimension, and "Organizational Factors" is the most Effect dimension among the dimensions influencing the readiness of IoT in industries. Additionally, "Security and Privacy" holds the highest importance among the Cause dimensions, while "Environmental Factors" holds the highest importance among the Effect dimensions. Table 6 illustrates the order of importance and priority of influential and affected dimensions.

Table 6
The amount of importance and relation between dimensions (cause and effect)

Cause / Effect	Dimensions
Cause	1- Security and Privacy, 2- Hardware Infrastructure, 3- Data Analytics
Effect	1- Environmental Factors, 2- Soft Infrastructure, 3- Organizational Factors, 4- Customers and Training, 5- Supply Infrastructure

3.1. Validation of Fuzzy AHP Assessments

In this evaluation, the prioritization of dimensions impacting the readiness for implementing IoT in industries has been conducted using the Fuzzy Analytic Hierarchy Process (AHP) method. The table 7 presents the rankings, weight percentages, normalized weights, and corresponding dimensions for the prioritization. According to the results obtained from the Fuzzy AHP and defuzzification steps, eight dimensions were considered for pairwise comparisons. The experts ranked the dimensions based on their importance, and the results indicate the following prioritization in Table 7. The dimensions have been ranked based on their weighted percentages, indicating their relative importance in the context of IoT implementation readiness. The findings reveal that certain dimensions hold higher significance compared to others. The dimension of organizational factors emerges as the most important dimension, with a weighted percentage of 24.237. Following organizational factors, the dimension of hard infrastructure, with a weighted percentage of 21.053, holds the second position. The dimension of soft infrastructure, ranked third with a weighted percentage of 20.941, underlines the importance of compatible software, platforms, integrated databases, and data analytics tools within the IoT ecosystem. Environmental factors, supply infrastructures, customer and training, security and privacy, and data analysis dimensions are also identified as relevant dimensions, albeit with relatively lower weighted percentages. However, it is important to note that these dimensions also play significant roles in the success of IoT implementation. Specifically, the security and privacy of information and data, accurate data analytics, and appropriate training for customers and employees hold high importance.

Table 7
The amount of importance and relation between dimensions (cause and effect)

Row	Dimensions	Normalized weight	Weight percent	rank
D4	Organizational factors	0.242	24.237	1
D2	Hard infrastructures	0.211	21.053	2
D1	Soft infrastructures	0.209	20.941	3
D5	Supply infrastructures	0.115	11.457	4
D3	Environmental factors	0.08	7.972	5
D7	Security and privacy	0.066	6.5981	6
D8	Data analytics	0.040	4.0112	7
D6	Customers and Training	0.037	3.7305	8

4. Conclusion

The rise of the information age and the emergence of digital technologies have brought forth various innovative concepts like Industry 4.0, smart health, digital services, and smart cities. In this evolving landscape, IoT technology has become one of the primary driving forces across different domains, engaging all stakeholders, particularly businesses, platforms, and industries. IoT goes beyond the mere connection of objects; it encompasses a holistic ecosystem and a continuous value chain that involve diverse aspects and factors working collaboratively toward its realization. This indicates which dimensions are influential and which are affected in IoT implementation. Therefore, businesses must evaluate the multifaceted factors and dimensions influencing IoT implementation. Considering the dimensions affecting the readiness of IoT implementation in industries, using multi-criteria decision-making techniques is very helpful for addressing important issues in this field. For this purpose, Fuzzy-AHP and Fuzzy DEMATEL methods have been used to rank and examine the cause-and-effect relationships of the dimensions affecting the readiness of IoT implementation in industries.

The findings of Fuzzy AHP assessment provide insights into the prioritization of dimensions influencing the readiness for IoT implementation in industries. The results highlight the significance of organizational factors and technical infrastructures, which play crucial roles in successful IoT implementation. Organizational factors highlight the critical role of organizational aspects such as managerial support, commitment, and awareness and the formulation of comprehensive plans, regulations, and standards for IoT implementation. Attention should be given to strengthening the organizational infrastructure and fostering a supportive environment to facilitate successful IoT integration in industries.

Additionally, hard and soft infrastructures, including networks, devices, software, and platforms, are vital for successful IoT deployment. This emphasizes the significance of physical and non-physical objects, robust internet access, network strength, data storage infrastructures, and adherence to IoT protocols and standards. Building a reliable and efficient hard infrastructure forms a crucial foundation for the successful deployment of IoT systems in industrial settings. This dimension highlights the need for seamless integration, efficient data management, and the availability of suitable software and platforms for IoT implementation. On the other hand, environmental factors, security and privacy, data analytics, and customer and training dimensions have relatively lower importance. These dimensions encompass cultural, social, regulatory, financial, and technological aspects that contribute to industry readiness for IoT implementation.

In conclusion, prioritizing dimensions based on the Fuzzy AHP analysis provides valuable insights for decision-makers and stakeholders involved in IoT implementation in industries. The findings underscore the significance of organizational factors, hard infrastructure, and soft infrastructure as critical dimensions to focus on when preparing for IoT integration. By considering these dimensions and addressing their respective factors, organizations can enhance their readiness and improve the chances of successful implementation, leading to enhanced operational efficiency, improved decision-making, and the realization of the full potential of IoT in industrial settings. Therefore, to achieve readiness in implementing IoT in industries, attention should be given to developing organizational factors, technical infrastructures, security and privacy, and data analytics. Furthermore, establishing a robust and resilient environment and optimizing customer satisfaction and training are crucial aspects to consider.

By considering the influential factors on IoT implementation, this study first introduces dimensions for evaluating IoT implementation readiness by examining these aspects and factors. These dimensions are derived from prior research on IoT readiness and consist of eight dimensions. Then, in the next step, these dimensions are provided to IoT experts in business, and they are asked to determine their importance and relationships. Through the collection of questionnaires and the use of Fuzzy sets, linguistic expressions are converted into Fuzzy numbers, and the results are analyzed using the Fuzzy DEMATEL method. The analysis reveals a causal relationship between dimensions, dividing them into two categories: influential and affected dimensions. Moreover, the importance of each dimension within each category is established, indicating which dimensions have a significant impact and which are influenced during IoT implementation. By comprehending the interrelationships and developing an appropriate plan, IoT implementation can be effectively guided.

The analysis results highlight the dimension of "security and privacy" as the most influential. In contrast, the dimension of "organizational factors" is identified as the most affected among the influential factors in IoT implementation. Within the influential dimensions’ category, "security and privacy" holds the highest priority, whereas "data analytics" has the lowest priority. In the affected dimensions category, "environmental factors" have the highest priority, while "supply and delivery infrastructure" have the lowest priority in terms of importance. These analysis findings indicate that industries need to determine which influential factors in IoT implementation they should prioritize. In the world of IoT, security and privacy are incredibly important. This includes both technical aspects like secure communication networks and data management, as well as environmental and organizational considerations like ethical and social concerns related to security. Therefore, industries and businesses must consider this dimension throughout the integrated IoT ecosystem.

Furthermore, considering the organizational dimension as the most affected, industries should align this dimension with other dimensions, including environmental aspects such as adopted laws and regulations, regulatory bodies, societal and cultural factors, and the government's special role. To transform business models and structures and meet customer needs, stakeholders, service providers, infrastructure, and data analysis should be considered. Industries should formulate their policies, goals, and strategies based on IoT implementation and consider each dimension's impact on IoT implementation within their industry or organization.

The Fuzzy DEMATEL and Fuzzy AHP methods offer additional perspectives on the factors that affect the readiness of IoT implementation in industries. Their results and analysis are complementary. Both methods highlight the importance of various dimensions and their cause-effect relationships. The Fuzzy DEMATEL analysis reveals that no single dimension has the most significant importance among the factors affecting IoT readiness. Instead, it identifies "Security and Privacy," "Data Analytics," and "Hardware Infrastructure" as significant cause dimensions, while "Environmental Factors," "Supply Infrastructure," "Soft Infrastructure," "Customers and Training," and "Organizational Factors” are considered as effect dimensions. This analysis assists in recognizing the connections and relationships between these dimensions. On the other hand, through the Fuzzy

AHP analysis, a prioritized ranking of the dimensions is obtained based on their weighted percentages. The readiness for implementing IoT is shaped by important dimensions such as "Organizational Factors," "Hard Infrastructures," and "Soft Infrastructures." Furthermore, it acknowledges the importance of "Security and Privacy," "Data Analytics," "Environmental Factors," "Supply Infrastructures," and "Customers and Training," although they are weighted with lower percentages.

Developers of IoT can gain valuable insights by combining the results of both methods. To prioritize their efforts effectively, they should consistently identify important dimensions like "Security and Privacy" and "Organizational Factors." To successfully implement IoT, it is important to address these dimensions. Furthermore, attention should be given to constructing robust "Hardware Infrastructure" and "Soft Infrastructure" components, as well as considering "Environmental Factors" and "Supply Infrastructures." The findings highlight the importance of having precise "Data Analytics" and providing sufficient "Customer and Training" support for the successful implementation of IoT. Developers can make informed decisions, allocate resources effectively, and enhance the overall readiness of IoT in industries by understanding the interdependencies and considering the identified dimensions.

To sum up, the Fuzzy DEMATEL and Fuzzy AHP analyses combined give a thorough understanding of the factors that impact IoT readiness. Having this knowledge can help developers prioritize their efforts, address critical factors, and make informed decisions to implement IoT in various industries successfully.

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Conflicts of Interest

The authors declare no conflicts of interest.

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