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Analyzing Barriers to Internet of Things (IoT) Adoption in Humanitarian Logistics: An ISM–DEMATEL Approach

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Abstract: *Background*: Effective humanitarian logistics (HL) is essential in disaster response. The "Internet of Things" (IoT) holds potential to enhance the efficiency and efficacy of HL, yet adoption is slowed by numerous barriers. *Methods*: This study employs interpretive structural modeling (ISM) and decision-making trial and evaluation laboratory (DEMATEL) to explore and classify barriers to IoT integration in HL. *Results*: A total of 12 barriers were identified, classified, and ranked according to their driving power and dependence. Key barriers include lack of standardization, organizational resistance, data quality issues, and legal challenges. *Conclusions*: Overcoming these barriers could significantly improve relief operations, reduce errors, and enhance decision-making processes in HL. This investigation is the first of its kind into IoT barriers in HL, laying the groundwork for further research and providing valuable insights for HL managers.

Keywords: IoT; humanitarian logistics; emergency responders; barriers; relief operations; organizational resistance

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1. Introduction

Humanitarian logistics (HL) plays a crucial role in delivering aid to disaster-stricken areas and protecting the most vulnerable populations [1–6]. According to Tomasini and Wassenhove [7], HL is defined as the "process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials as well as related information from the point of origin to the point of consumption for the purpose of alleviating the suffering of vulnerable people" (p. 550). The purpose of HL is to reduce damage caused by a catastrophe and provide timely responses to the needs of those who are affected [8–11]. As a result of the unpredictability of demand in disaster-stricken areas, HL faces unique challenges not encountered by business logistics [12,13]. Generally, HL focuses primarily on effectiveness despite the growing importance of reducing costs and achieving cost savings [14]. Since providing aid requires cooperation between several stakeholders, including humanitarian and military organizations, non-governmental agencies, and local authorities [15,16], it is crucial that participants in HL networks have aligned incentives and objectives [17]. While those involved in business logistics typically work in a relatively stable atmosphere and are motivated by profit, those involved in HL must frequently deal with supply chain disruptions that necessitate coordinated efforts to save lives and provide relief to vulnerable individuals [18,19]. As a result, it is imperative to effectively address the various aspects of HL, including the unpredictability of demand in terms of size, time, and location; the sudden high demand for a wide range of supplies with limited lead time; the high importance placed on timely deliveries, and the scarcity of resources such as finance, technology, personnel, and infrastructure [20–22].

Improvements in humanitarian organizations' efficiency and effectiveness have been essential to the continuation of HL activities, and modern means of communication and technologies have played a crucial role in this regard [23–30]. Recently, the emergence of the Internet of Things (IoT) has been considered a key enabler for HL [31,32]. Conceptually, IoT represents a rapidly growing technology that involves a network of interconnected, intelligent, and autonomous devices [33,34]. Its purpose is to boost efficiency, profitability, and productivity through the use of big data technologies [35] and predictive analysis techniques [36]. IoT has transformed the traditional corporate environment into a digitally sophisticated digital ecosystem.

The rise of IoT has affected all industries, with the most notable impact being seen in the realm of HL [37]. IoT technology has made it possible for devices and machines to be connected and communicate with each other, leading to a multitude of applications and use cases in various industries [38–40]. While its impact can be felt across all sectors, the HL field is particularly well suited to reap the benefits of IoT, as the technology can help streamline humanitarian processes, maximize efficiency, and, ultimately, better serve the needs of the victims. Similarly, the technology has already been tested in the field, in the form of sensors on bridges in flood-prone areas and smart thermometers for medicine transportation [41]. For example, in Rwanda, SweetSense is placing WiFi or cellular-connected IoT sensors on water pumps to register data about water supply and demand, hourly flow rates, usage, performance, seasonality, and peak periods, thereby increasing the uptime of hand pumps by 80–90%, ensuring a more stable flow of water in villages, and alleviating drought conditions [42]. Furthermore, IoT sensors play a role in the 'Global Alliance for Clean Cookstoves' initiative by measuring black carbon emitted by stoves, thereby supporting projects that disseminate improved cookstoves and aim to reduce indoor air pollution. Additionally, integrating these clean stoves into international development projects ensures that refugee camps, disaster relief operations, and long-term aid efforts serve as vital distribution networks [43]. Finally, STAMP2 sensors collect patient data, such as electrocardiogram (ECG), heart rate, oxygen saturation, temperature, and respiratory rate data in areas with outbreaks like Ebola, acting as a 'Smart Band-Aid' and improving response times in critical areas [44].

According to Yang et al. [45], the use of IoT in HL offers a real-time and complete solution for monitoring personnel and resources, improving visibility in indoor and outdoor environments, and ensuring accurate accountability of HL resources during emergency response operations. As increased situational awareness can lead to more effective decisions in HL operations [46], IoT has the capability to collect real-time and thorough information about the disaster site through the utilization of radio frequency identification (RFID) and wireless sensor networks. Consequently, emergency personnel can attain quick and precise situational awareness by collecting and accessing extensive information regarding the disaster emergency [45]. Moreover, IoT allows for the tracing, tracking, and monitoring of response personnel and their resources, providing visibility into their availability. This enables a more efficient allocation and delivery of resources to the disaster site and enhances the capability of HL operations by increasing resource access to a greater number of humanitarian activities. Through its instant monitoring capability, IoT facilitates information exchange and real-time updates on the status of a disaster area and the availability of an individual organization's resources. Therefore, the IoT's data architecture can be invaluable in strengthening collaboration across several organizations involved in HL [47].

Despite the vast potential of IoT to create an online system for direct interactions and transactions between HL stakeholders, such as humanitarian organizations, first responders, logistics providers, governments, etc. [45], the adoption of the technology in HL is still in its early phase [36]. More precisely, the literature is deficient in research on the adoption of IoT in HL. Given the current rise in human suffering in recent years, due to the increasing frequency and severity of natural catastrophes [32], research on the impact of IoT on HL is more essential than ever. HL stakeholders should recognize the importance of IoT in supporting humanitarian actions control, reducing HL inefficiencies, increasing compliance, and leading to significant advances in disaster response and recovery [24]. Adopting IoT enables the development of a HL system that can forecast disaster occurrence and resource demand, increase emergency preparedness, and improve the overall coordination and collaboration between various HL stakeholders [48]. Currently, the practitioners in the HL field recognize the advantages of IoT in their relief operations and are prepared to use this technology. The research problems addressed in the current study are the following:

- There is a lack of comprehensive understanding about the key barriers to the adoption of IoT in the HL field. While IoT has immense potential to revolutionize HL operations by enhancing interactivity, transaction efficiency, and decision-making among various stakeholders, its adoption is still in the nascent stage. Despite the recognition of IoT's advantages by practitioners, they confront numerous challenges and barriers, both technological and managerial, which inhibit its widespread adoption in HL [32,49].
- The second problem is the dearth of scholarly research that investigates the interrelationships and influences among these barriers. A holistic understanding of how these barriers interact and influence each other is essential to develop effective strategies for mitigating them and fostering IoT adoption in HL.

In response to these problems, the present study aims to identify and analyze the key barriers to IoT adoption in HL, using the interpretive structural modeling (ISM) and decision-making trial and evaluation laboratory (DEMATEL) techniques. The incorporation of both the ISM and DEMATEL techniques into this study is based on the complementary nature of these methods and their unique strengths in addressing the research objectives. The ISM technique is an effective tool for identifying relationships among factors and constructing a hierarchical structure of complex systems [50]. It provides valuable insights into the dependencies and driving powers of the identified barriers to IoT adoption in HL. This helps to develop a preliminary understanding of how these barriers are connected and influence each other. While ISM is instrumental in building a hierarchical relationship among barriers, it falls short in quantifying the degree of influence among them [51]. To fill this gap, the DEMATEL technique is employed. DEMATEL extends the ISM approach by quantitatively measuring the interactive effects of the barriers, providing a more nuanced understanding of their interdependencies [52]. It allows us to identify the most influential barriers, distinguishing them into 'cause' and 'effect' groups [51]. This is particularly valuable in formulating targeted strategies for overcoming these barriers. Thus, the combination of ISM and DEMATEL allows the study to create a comprehensive and robust analysis of the barriers to IoT adoption in HL, encompassing both qualitative relationships and quantitative influences among these barriers [53].

The following sections of the paper are structured as follows. Section 2 provides a concise overview of IoT, its potential for HL, and the barriers hampering its adoption in this field. Section 3 describes the research method applied. Section 4 elaborates on the application of the ISM–DEMATEL approach in HL, and is followed by the findings. Section 5 presents the discussion of the results and their implications. Finally, we briefly conclude the study, highlighting its limitations and future research directions.

2. Conceptual Background

2.1. The IoT Concept

The IoT, which refers to devices that are connected to the internet and can collect information about the environment, has seen quick growth because of the widespread use of advanced hardware and software, better access to communication networks, and improvements in data analysis tools [54–56]. The basic idea behind IoT is to connect various devices that produce or gather data through technologies such as RFID, actuators, sensors, and smartphones, so that these devices can communicate with each other [57]. IoT has a three-layer structure, including (1) the physical or perception layer, (2) the network layer, and (3) the application layer. The physical layer collects information about the environment, which is used by platforms to perform algorithms or offer services [58]. The network layer, considered the heart of IoT, is responsible for transmitting and processing the information obtained by the perception layer [59,60]. Unlike the network layer, the application layer consists of a set of functionalities and services offered to the users [58]. As the topmost layer of the IoT architecture, this layer encompasses two sublayers: (1) the application support platform, and (2) the application sublayer [61]. The application support platform sublayer plays a crucial role in facilitating information collaboration, sharing, and interoperability among devices and systems in the IoT network. This sublayer also helps to ensure seamless communication and data exchange between the different components of the network, thereby enabling the efficient delivery of services and applications [58]. On the other hand, the application sublayer represents the various applications and services that are used by different industries and businesses. This sublayer includes a wide range of applications, including smart logistics, energy management, smart supply chain management, smart parking, and smart transportation [33,34,54,57]. These applications utilize the data collected by the physical layer and processed by the network layer to offer a range of value-added services to users, such as optimizing logistics operations, maximizing energy efficiency, and supporting smart transportation systems [62–64].

2.2. IoT Applications in HL

The constantly changing needs and circumstances during a relief operation highlight the importance of making quick and accurate decisions efficiently [65]. As a result, the integration of IoT is essential to support effective disaster management planning in HL. With its ability to instantly communicate updated information, IoT can play a crucial role in enabling dynamic workflow adaptations. In the realm of disaster management, the use of IoT solutions can provide crucial information needed for effective relief planning following a natural disaster [47]. Moreover, IoT can support environmental surveillance and disaster relief due to its service-oriented architecture for monitoring and detection [66]. IoT networks can offer solutions for monitoring and managing emergency scenarios, which currently lack accurate information about the emergency site. The use of dedicated IoT sensors, along with smart cameras, wireless systems, and GPS, enables real-time localization [67], monitoring [68], and the development of a full map of the disaster scenario to predict its trends (e.g., the velocity of fire spread), which all help to plan emergency rescue activities. According to Khan et al. [66], IoT represents an effective tool for detecting catastrophic events by offering intelligent aggregation, multi-source alignment, and assessment of information, which are crucial steps in gaining situational awareness and making informed decisions. Greco et al. [69] demonstrate how the integration of IoT and semantic web techniques can lead to a successful implementation of earthquake event detection. Their approach involves annotating information collected from web services and IoT-based sensors, allowing for a more efficient method of detecting earthquakes. In their study, Wen et al. [70] propose the use of IoT to create an emergency food logistics information system. The system relies on IoT to provide unique identification and tracking of food, which helps to gather and process information about food supply and demand, and to optimize emergency food distribution. In this way, the system ensures food safety and preservation while also ensuring that emergency food is distributed in a timely and efficient manner, according to actual needs and without shortages or excess. Al-Turjman [71] puts forward a cognitive data delivery framework to tackle the difficulties that arise during large-scale network failures during disasters. Based on the findings, the author suggests that an IoT-based framework can improve the current network status through optimization.

The implementation of IoT in HL can greatly improve the way disaster risk management processes are carried out, leading to quicker predictions of natural hazards (e.g., landslides, rockfall, earthquakes, etc.), more effective response, and cost-effective decision-making in recovery [72]. For example, IoT provides real-time information about the earthquake event, its destructive impact, the situation in the affected area, and the locations of victims, which are crucial for disaster risk management agencies to carry out rapid response operations and minimize the impact on those affected [73]. Furthermore, the implementation of IoT can bring about accurate and monitored data flow in service-oriented organizations, which is essential for enhancing resilience in humanitarian supply chains [74]. Reaidy et al. [75] state that the incorporation of IoT into inventory management can improve various relief practices and enhance the coordination between strategies, resulting in improved performance and increased resilience in the event of humanitarian supply chain disruption. Information sharing through IoT is critical in facilitating cooperation between the upstream and downstream operations of the humanitarian supply chain by providing a large volume of data and flexibility in response to changing demands [76]. During a disaster, ineffective coordination in inventory management for logistic relief can be a major challenge. For this reason, there is a need for IoT to develop a new logistics inventory business process in the shortest response time to ensure rapid disaster relief distribution [77].

When combined with web technologies and advanced technologies, such as artificial intelligence (AI) and big data analytics, IoT provides solutions for monitoring potential disaster scenarios in real time [78]. As such, IoT-based solutions are demonstrating efficacy in detecting and monitoring disasters, such as earthquakes, landslides, and forest fires [79–81]. The collaboration between IoT, wireless sensor networks, and unmanned aerial vehicles also has the potential to enhance real-time tracking, analytics, and decision-making to aid smart cities in meeting public safety demands in the event of a disaster [29,82,83]. Similarly, IoT can be combined with blockchain to facilitate prompt payments and provide a higher level of control and visibility over transactions performed by HL actors. As a result, this would lead to a reduction in transaction costs and minimal tampering risks while increasing trust in HL [32]. Overall, the use of IoT in HL can help minimize and prevent disaster risks through real-time monitoring and communication; it can also enhance emergency response through real-time assistance and timely responses, and aid in post-disaster efforts, such as searching for missing persons through the internet. The dynamic and challenging terrain situations often encountered in disasters emphasize the need for efficient and appropriate decision-making in limited time, and IoT, with its ability to deliver the latest real-time information, can be instrumental in creating an effective workflow in HL [65].

2.3. Barriers to IoT Adoption in HL

- Cost (B1): The high implementation cost of IoT in HL is a significant adoption barrier, particularly for budget-restrained organizations and those in developing countries [66]. This encompasses hardware and software costs [65,84,85], data management [66], and maintenance [24]. High initial costs may deter investment in IoT, causing organizations to miss out on potential benefits [32,65,86].
- Technical complexity (B2): The complexity of integrating various IoT components presents significant challenges in HL [66,87,88]. Ensuring data safety and accuracy is crucial [23,88]. Additionally, operating IoT in remote and harsh environments can add to the complexity [32,89,90].
- Interoperability (B3): Interoperability issues hinder the widespread use of IoT in HL [90–92]. Data sharing problems between devices can negatively affect aid delivery [32]. Vendor lock-in due to lack of interoperability can limit scalability and raise costs [93].
- Data privacy and security (B4): Concerns about data security and privacy are paramount for safe and responsible IoT use in HL [23,88,94]. The risk of data breaches and privacy issues must both be addressed [66,86,90].
- Network availability (B5): Limited network availability in remote areas poses a major barrier to IoT use in HL [90,95]. Disruptions due to natural disasters or conflicts can hinder effective coordination and management [31].
- Lack of power (B6): Limited power availability impedes the adoption of IoT in HL [66,84,90]. This constraint can affect the continuous and efficient use of IoT, especially in regions lacking reliable electricity sources [96].
- Lack of standardization (B7): The absence of standardization in IoT technologies poses a considerable challenge to HL [24,86]. Standardization ensures interoperability and compatibility between devices, which is critical for streamlining operations [97].

- Data quality and accuracy (B8): Concerns about data quality and accuracy pose substantial hurdles to IoT adoption in HL [88,98]. Errors and inaccuracies can negatively impact the efficacy of operations [84,90].
- Integration with existing systems (B9): Integrating IoT with existing systems in humanitarian organizations can be a formidable task, potentially leading to data silos and inefficient operations [23,54,65,99].
- Legal and regulatory challenges (B10): Legal and regulatory restrictions can significantly hinder IoT adoption in HL [65,100]. These can include privacy regulations, restrictions on technology use, and transportation regulations across borders [32,86,90].
- Human capacity (B11): Limited human capacity to effectively use IoT technology can impede its adoption in HL [23,88,96]. This includes the need for skills and knowledge to operate and maintain IoT systems [100].
- Organizational resistance (B12): Resistance to change within organizations can present a significant barrier to IoT adoption in HL [101]. Factors such as lack of familiarity with IoT, fear of change, and cost concerns can contribute to this resistance [88,102].

3. Research Method

The present research utilized a hybrid methodology consisting of two phases, namely the interpretive structural modeling (ISM) and decision-making trial and evaluation laboratory (DEMATEL). The ISM approach was utilized to construct a multi-level hierarchical structure that identified the relationship among different factors, enabling the comprehension of complex relationships and prioritizing the factors under consideration. To quantitatively measure the interactive effects of the factors, DEMATEL was used.

Although other methodologies, such as the analytic hierarchy process (AHP) and fuzzy cognitive maps (FCM), also offer robust frameworks for analyzing complex decisions and simulating causal relationships, respectively [103,104], ISM–DEMATEL was chosen for its proven effectiveness in mapping and quantifying the intricate web of relationships among barriers to technology integration. AHP provides a structured technique for organizing and analyzing complex decisions through pairwise comparisons, and could have offered a different perspective on the prioritization of barriers [105]. Meanwhile, FCM could have been utilized to model the causal dynamics among the barriers, providing insights into how changes in one factor might impact others over time [106]. The decision to employ ISM–DEMATEL was based on a comprehensive consideration of the methodology's strengths in addressing the research questions, particularly its capacity to elucidate the complex relationships among barriers to IoT integration in HL, and to quantify these interactions for more nuanced analysis and prioritization.

In the academic literature, several scholars applied the ISM–DEMATEL approach to investigate a wide variety of topics. For example, Kumar and Dixit [107] utilized ISM and DEMATEL to identify and understand the hierarchical and contextual relationships among barriers to e-waste management. The study illuminated the mutual relationship between, and interlinking among, the barriers, highlighting the lack of public awareness about e-waste recycling and the lack of policies addressing e-waste issues as root cause barriers.

Similarly, Xie and Liu [108] combined ISM and DEMATEL to establish a hierarchical structure of factors influencing escalator-related incidents, and distinguished cause factors from effect factors. The study found that factors such as safety education, behavior, and safety rules are the most influential, and asserted that management priority should be given according to the hierarchy level and the interaction of factors. Another study [109] applied the ISM–DEMATEL method to study the critical success factors of knowledge management in Iranian urban water and sewage companies. Among the studied factors, strategies and goals had the greatest impact on success, followed by senior management support, teamwork, and organizational culture. Manoharan et al. [110] used an integrated approach of ISM and DEMATEL for the identification and ranking of the drivers and barriers in the implementation of the circular economy in the automobile industry. The study found that share/benefit and reduction of cost are the most critical drivers, and that unaware/limited knowledge and cost and financial constraint are the major barriers. Finally, Alzarooni et al. [53] used the combined approach to identify the enablers of digital supply chain in the literature and explored the contextual relationship between them. The study found that "smart warehousing" is the most influential enabler, with high driving power and weak dependence power. These studies support the value of the combined ISM–DEMATEL approach in various contexts, underpinning its appropriateness for analyzing the barriers to IoT adoption in HL.

Before beginning our research, we ensured that we obtained all necessary ethical clearances. We strictly followed the guidelines to maintain the highest standards of research ethics throughout our study. All data used in our research were collected responsibly, ensuring the anonymity and confidentiality of the participants involved. No personally identifiable information was collected or used at any point. Also, we ensured that our study did not harm the participants in any way, and we took all the necessary precautions to avoid any potential bias in our findings. Detailed descriptions of the ISM and DEMATEL methodologies are provided below.

3.1. The ISM Methodology

The ISM was proposed by Warfield [111] to develop a comprehensive framework for connecting attributes. The methodology employs an interactive learning process in which a group of disparate elements are directly related and organized to develop a systematic model [112]. The ISM model captures the configuration of a complex issue, system or domain of study, using words, graphics, and discrete mathematics, and serving as a multi-criteria decision-making tool for examining interactions and interrelationships [113]. The ISM technique utilizes the experience, expertise, and knowledge of experts to divide a complex system into several sub-systems or elements and form a multi-level structural model [114]. This approach enhances both direct and indirect relationships, which increases the accuracy of the factors under consideration, unlike when they are considered in isolation from one another.

The methodology employed in this study to implement the ISM model is outlined in a step-wise manner [115]. Initially, the barriers to IoT adoption in HL were identified through a literature review and validated by expert opinions. Then, a relationship was established among all the identified barriers. To develop a pair-wise relationship among barriers to IoT adoption, the researchers employed a structural self-interaction matrix (SSIM), comprising four symbols (V, A, X, and O) that represent the direction of the relationship between the barriers (i and j).

- V indicates that barrier i impacts barrier j.
- A indicates that barrier i is impacted by barrier j.
- X indicates that barrier i and j impact each other.
- O indicates that barrier i and j do not impact each other.

Using the SSIM, an initial reachability matrix was developed and tested for transitivity. The initial reachability matrix was constructed using binary values (0 and 1) derived from the symbols in the SSIM, as per the following guidelines.

- V was converted to 1 in the (i, j) entry of the matrix, and to 0 in the corresponding (j, i) entry.
- A was converted to 0 in the (i, j) entry, and to 1 in the corresponding (j, i) entry.
- X was converted to 1 in both the (i, j) and (j, i) entries.
- O was converted to 0 in both the (i, j) and (j, i) entries.

The final reachability matrix is generated by ensuring transitivity, where a barrier 'A' is considered similar to 'C' if it is related to 'B' and 'B' is related to 'C'. This matrix is then partitioned into levels and used to construct a directed graph. Transitive links are eliminated from the graph, and the nodal elements are replaced with statements to create the ISM model for barriers to IoT adoption in HL. The model is reviewed and checked for conceptual inconsistencies.

3.2. The DEMATEL Methodology

The DEMATEL method utilizes matrices to represent the contextual relationship and the intensity of elements' influence on the target system, resulting in observable structural models that illustrate the cause-effect relationship of elements. Consequently, the DEMATEL method has been widely utilized in various fields, including healthcare [52], social media [116], emergency management [117], smart city [118], renewable energy [119], and blockchain technology [51]. The DEMATEL method provides several advantages that can aid researchers in gaining a better understanding of the nature of the problem.

The DEMATEL procedures are explained in a step-by-step manner in several sources, such as Shieh et al. [52] and Sumrit and Anuntavoranich [120]. The first step involves calculating the average matrix.

To collect data for the SSIM, each expert in the panel was asked to evaluate the direct influence between any two success factors, using a scale of 0 to 3. A score of 0 meant no influence, while 1, 2, and 3 indicated low, medium, and high influence, respectively. The notation x_{ij} represents the expert's assessment of how much factor i affects factor j.

When i equals j, the diagonal elements are set to zero. A non-negative n by n matrix can be created for each respondent as $X^k = \left[x_{ij}^k\right]_{n \times n}$, where k ranges from 1 to H, representing the number of respondents, and n is the number of factors. Thus, $X^1, X^2, \cdots, X^{n-1}, X^n$, and so on are the matrices from the H respondents. To combine the opinions of all H respondents, an average matrix $A = \left[a_{ij}\right]_{n \times n}$ can be formed as:

$$a_{ij} = \frac{1}{H}\sum_{k=1}^{H} x_{ij}^k$$

The second step involves calculating the normalized initial direct-relation matrix $N = \lambda A$, where $\lambda = \frac{1}{\max\limits_{1 \leq i \leq n} \sum_{j=1}^{n} a_{ij}}$. The elements in the N matrix range between 0 and 1. The third step involves computing the total relation matrix T using the formula $T = N\,(I - N)^{-1} = \left[t_{ij}\right]_{n \times n}$, where I is the identity matrix.

Assuming that vector $R = \left[R_j\right]_{1 \times n}$ and $D = \left[D_i\right]_{n \times 1}$, the sum of the row can be computed as:

$$D = \begin{bmatrix} D_1 \\ D_2 \\ D_3 \\ \vdots \\ D_n \end{bmatrix} \text{ with } D_i = \sum_{j=1}^{n} t_{ij} \text{ where } i = 1, 2, 3, \cdots, n$$

To determine the column sum, the following calculation is performed:

$$R = \left[R_1, R_2, R_3, \ldots, R_n\right] \text{ with } R_j = \sum_{i=1}^{n} t_{ij} \text{ where } j = 1, 2, 3, \cdots, n$$

By computing the sum of the row, it is possible to determine the combined direct and indirect influence of factor i on the remaining factors. The column sums reflect the direct and indirect impacts of other factors on factor j. In cases where i = j, the sum of D_i and R_i provides a comprehensive overview of the total effects that factor i receives and gives, as follows:

$$D_i + R_i = \sum_{j=1}^{n} t_{ij} + \sum_{j=1}^{n} t_{ji}$$

The value of factor i in the entire system reflects its degree of importance. The difference between D_i and R_i indicates the net effect of factor i on the system.

$$D_i - R_i = \sum_{j=1}^{n} t_{ij} - \sum_{j=1}^{n} t_{ji}$$

If $(D_i - R_i)$ is positive, then factor i is a net cause; while if it is negative, factor i is a net receiver. The final step in the DEMATEL method is to create an impact relation matrix that visualizes the complex interrelationships between all the coordinate sets of $(D_i + R_i)$ and $(D_i - R_i)$. This map helps researchers identify the most significant factors that influence decision-making [50].

4. Results and Analysis

This section explains the methodology used to analyze the relationship between barriers to IoT adoption in HL using ISM and DEMATEL. The development of the ISM model and MICMAC analysis are presented, followed by the results of DEMATEL.

4.1. Results of ISM

To identify the significant barriers to IoT adoption in HL, the research team consulted secondary data sources and experts in the fields of technology, computer science, HL, and supply chain management. The team reviewed a pool of journals from various databases, including Scopus, Web of Science, Springer, IEEE Explore, Taylor and Francis, as well as book chapters, conference proceedings, corporate white papers, and magazines. The identified barriers were validated by a diverse group of 14 experts. The selection process for these experts involved a preliminary screening of their academic and professional profiles and contributions to the relevant fields, after which they were reached out to, via emails and LinkedIn messages. This outreach was aimed at gauging their interest and availability to participate in the validation process. The experts who expressed interest were then provided with an overview of the study and the role they would play in it, ensuring they had a clear understanding of the expectations and the study's objectives.

The demographics of the group were varied, contributing to a wide range of perspectives. The group consisted of nine males and five females, with a spread across different age groups (Table 1). In the study, three of the experts were under thirty, six were between thirty–forty-years-old, two were in the forty–fifty-years-of-age range, and three were over fifty-years-of-age. The educational backgrounds of these experts were also diverse, with two bachelor's degree holders, nine master's degree holders, and three Ph.D holders. In terms of their work experience, three experts had between five–ten years of experience, seven had ten–twenty years of experience, while four had more than twenty years of experience. Their expertise spread across multiple fields related to the study. A total of three were senior professors from academia, five were experienced integrators of complex systems in humanitarian logistics (HL), three were senior-level experts in the HL field, two were data analysts, and one was a senior manager specializing in IT security. The careful selection and outreach process ensured a thorough and comprehensive validation of the identified barriers by leveraging the diverse expertise and perspectives of the participants. Their collective insights were instrumental in validating the identified barriers.

The researchers shortlisted twelve barriers for the study, and the same group of experts provided their feedback on these barriers to develop the SSIM. The researchers, based in Saudi Arabia, moderated the discussions and compiled the information collected for preparing the SSIM. The authors made sure that the number of selected experts for the validation of the barriers and qualitative survey was constrained to a range of 10 to 50 experts, in accordance with prior studies [121,122].

Table 1. Demographic information of consulted experts.

Variables	**Number (*n* = 14)**
Gender	
Male	9
Female	5
Age	
Less than 30 years	3
30–40 years	6
40–50	2
Over 50 years	3
Educational level	
Bachelor	2
Master	9
Ph.D.	3
Years of experience	
5–10 years	3
10–20 years	7
20 years and above	4
Expertise field	
Academia	3
Complex system integration	5
Humanitarian logistics and supply chain managers	3
Data science	2
IT security	1

Experts provided input that was used to create the SSIM, which can be seen in Table 2 [121]. The ISM process is explained in Section 3.1, and the steps detail how to obtain the SSIM.

Table 2. SSIM.

Barriers	**B12**	**B11**	**B10**	**B9**	**B8**	**B7**	**B6**	**B5**	**B4**	**B3**	**B2**	**B1**
B1	X	A	V	A	A	V	V	X	X	X	X	
B2	X	O	V	A	A	V	V	X	X	X		
B3	X	O	V	A	A	V	V	A	X			
B4	X	A	V	A	A	V	V	X				
B5	X	A	V	A	A	V	V					
B6	O	O	V	O	O	O						
B7	A	O	V	O	A							
B8	V	A	V	A								
B9	V	A	V									
B10	A	A										
B11	V											
B12												

The SSIM is used to create the initial reachability matrix, as seen in Table 3.

Table 3. Initial reachability matrix.

Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
B1	1	1	1	1	1	1	1	0	0	1	0	1
B2	1	1	1	1	1	1	1	0	0	1	0	1
B3	1	1	1	1	0	1	1	0	0	1	0	1
B4	1	1	1	1	1	1	1	0	0	1	0	1
B5	1	1	1	1	1	1	1	0	0	1	0	1
B6	0	0	0	0	0	1	0	0	0	1	0	0
B7	0	0	0	0	0	0	1	0	0	1	0	0
B8	1	1	1	1	1	0	1	1	0	1	0	1
B9	1	1	1	1	1	0	0	1	1	1	0	1
B10	0	0	0	0	0	0	0	0	0	1	0	0
B11	1	0	0	1	1	0	0	1	1	1	1	1
B12	1	1	1	1	1	0	1	0	0	1	0	1

Transitivity was included in the ISM process using MATLAB software(version R2022b), and the final reachability matrix is presented in Table 4.

Table 4. Final reachability matrix.

Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
B1	1	1	1	1	1	1	1	0	0	1	0	1
B2	1	1	1	1	1	1	1	0	0	1	0	1
B3	1	1	1	1	1 *	1	1	0	0	1	0	1
B4	1	1	1	1	1	1	1	0	0	1	0	1
B5	1	1	1	1	1	1	1	0	0	1	0	1
B6	0	0	0	0	0	1	0	0	0	1	0	0
B7	0	0	0	0	0	0	1	0	0	1	0	0
B8	1	1	1	1	1	1 *	1	1	0	1	0	1
B9	1	1	1	1	1	1 *	1 *	1	1	1	0	1
B10	0	0	0	0	0	0	0	0	0	1	0	0
B11	1	1 *	1 *	1	1	1 *	1 *	1	1	1	1	1
B12	1	1	1	1	1	1 *	1	0	0	1	0	1

1 * entry included to incorporate transitivity.

From this matrix, the reachability set, antecedent set, and intersection sets were derived to determine the hierarchical levels. The barriers that are identified as top-level in the ISM hierarchy are those that have the same reachability and intersection sets. After the top-level barriers are identified, they are separated from the other barriers, and additional levels are established. The process used to determine all the hierarchical levels is shown in Table 5, and the resulting ISM model is displayed in Figure 1. As can be observed from the figure, the twelve barriers to IoT adoption in HL are classified into six hierarchical levels.

To gain further insights into the relationships revealed by the ISM model, the Matrice d'Impacts Croisés-Multiplication Appliquée à un Classement (MICMAC) analysis was used. This analysis evaluated the driving and dependence power values for the identified barriers based on the final reachability matrix in Table 3. The MICMAC diagram classifies the critical barriers into four clusters: autonomous barriers, dependent barriers, linkage barriers, and driving barriers. The driving and dependence values of all the barriers are plotted in Figure 2.

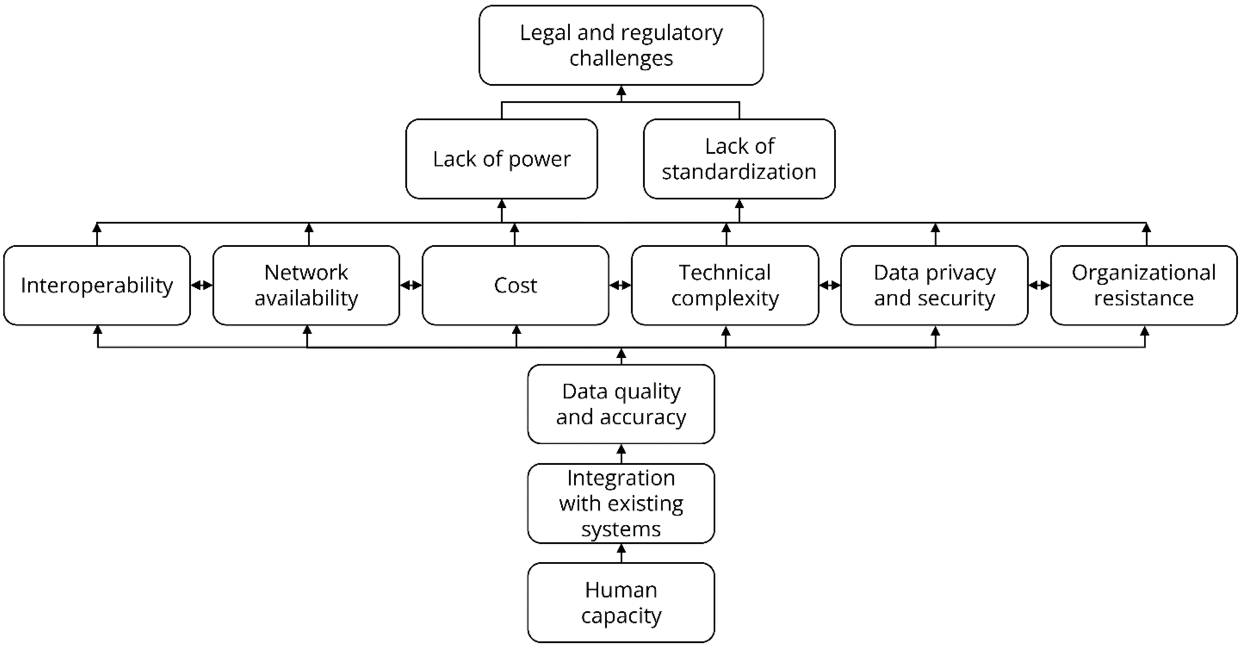

Figure 1. ISM model of IoT adoption barriers in HL.

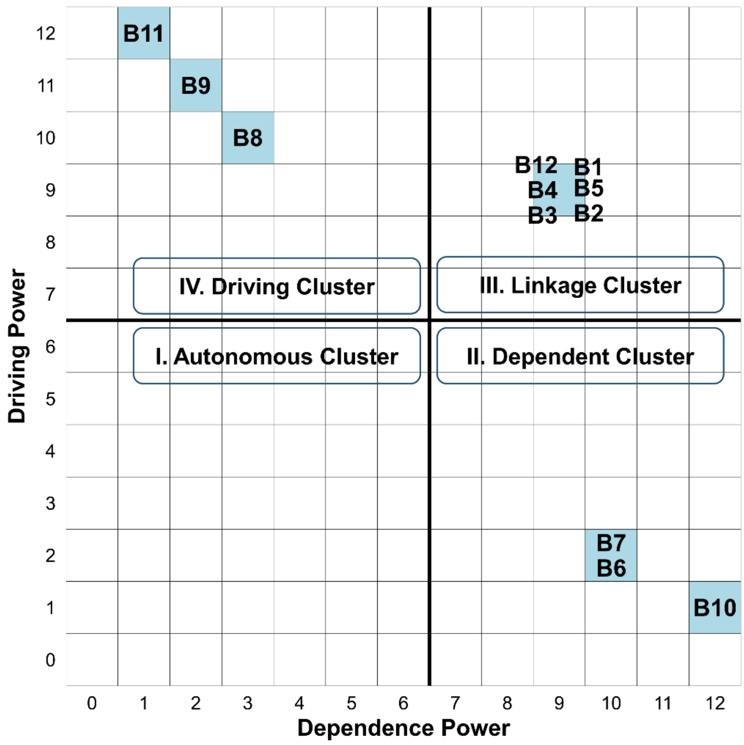

Figure 2. MICMAC diagram for barriers to IoT adoption in HL.

Table 5. Final level partitions.

Iterations	Reachability Set	Antecedents Set	Intersection Set	Level
Iteration no. 1	1,2,3,4,5,6,7,10,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
	1,2,3,4,5,6,7,10,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
	1,2,3,4,5,6,7,10,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
	1,2,3,4,5,6,7,10,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
	1,2,3,4,5,6,7,10,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
	6,10	1,2,3,4,5,6,8,9,11,12	6	
	7,10	1,2,3,4,5,7,8,9,11,12	7	
	1,2,3,4,5,6,7,8,10,12	8,9,11	8	
	1,2,3,4,5,6,7,8,9,10,12	9,11	9	
	10	1,2,3,4,5,6,7,8,9,10,11,12	10	I
	1,2,3,4,5,6,7,8,9,10,11,12	11	11	
	1,2,3,4,5,6,7,10,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
Iteration no. 2	1,2,3,4,5,6,7,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
	1,2,3,4,5,6,7,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
	1,2,3,4,5,6,7,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
	1,2,3,4,5,6,7,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
	1,2,3,4,5,6,7,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
	6	1,2,3,4,5,6,8,9,11,12	6	II
	7	1,2,3,4,5,7,8,9,11,12	7	II
	1,2,3,4,5,6,7,8,12	8,9,11	8	
	1,2,3,4,5,6,7,8,9,12	9,11	9	
	1,2,3,4,5,6,7,8,9,11,12	11	11	
	1,2,3,4,5,6,7,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	
Iteration no. 3	1,2,3,4,5,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	III
	1,2,3,4,5,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	III
	1,2,3,4,5,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	III
	1,2,3,4,5,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	III
	1,2,3,4,5,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	III
	1,2,3,4,5,8,12	8,9,11	8	
	1,2,3,4,5,8,9,12	9,11	9	
	1,2,3,4,5,8,9,11,12	11	11	
	1,2,3,4,5,12	1,2,3,4,5,8,9,11,12	1,2,3,4,5,12	III
Iteration no. 4	8	8,9,11	8	IV
	8,9	9,11	9	
	8,9,11	11	11	
Iteration no. 5	9	9,11	9	V
	9,11	11	11	
Iteration no. 6	11	11	11	VI

4.2. Results of DEMATEL

The connection among the 12 barriers to IoT adoption in HL was established using DEMATEL, a methodology that calculates the level of influence of each barrier on the others. To develop the direct influence matrix, normalized direct influence matrix, total relation matrix, and degree of influences, we implemented all the steps of the DEMATEL process described in Section 3.2. Tables 6–9 present the results of the DEMATEL process. The relationships between the barriers to IoT adoption in HL were derived from the degree of influence and are illustrated in Figure 3 using a diagram.

Table 6. Direct influence matrix.

Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
B1	0	2	2	1	2	2	1	2	2	2	2	2
B2	1	0	3	2	2	3	3	1	2	2	2	1
B3	1	3	0	2	2	1	2	2	3	1	1	2
B4	2	2	2	0	1	1	2	3	2	3	2	1
B5	2	2	1	1	0	2	1	1	2	1	2	1
B6	1	2	2	1	2	0	2	1	1	1	1	2
B7	1	3	3	2	1	1	0	2	3	2	2	2
B8	1	3	3	3	2	1	2	0	2	2	1	2
B9	1	3	3	2	2	1	2	2	0	1	2	2
B10	1	2	2	3	2	1	2	2	2	0	1	2
B11	1	3	2	1	1	1	2	2	2	2	0	3
B12	2	3	3	1	1	1	2	1	3	2	3	0

Table 7. Normalized direct influence matrix.

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
B1	0.000	0.091	0.091	0.045	0.091	0.091	0.045	0.091	0.091	0.091	0.091	0.091
B2	0.045	0.000	0.136	0.091	0.091	0.136	0.136	0.045	0.091	0.091	0.091	0.045
B3	0.045	0.136	0.000	0.091	0.091	0.045	0.091	0.091	0.136	0.045	0.045	0.091
B4	0.091	0.091	0.091	0.000	0.045	0.045	0.091	0.136	0.091	0.136	0.091	0.045
B5	0.091	0.091	0.045	0.045	0.000	0.091	0.045	0.045	0.091	0.045	0.091	0.045
B6	0.045	0.091	0.091	0.045	0.091	0.000	0.091	0.045	0.045	0.045	0.045	0.091
B7	0.045	0.136	0.136	0.091	0.045	0.045	0.000	0.091	0.136	0.091	0.091	0.091
B8	0.045	0.136	0.136	0.136	0.091	0.045	0.091	0.000	0.091	0.091	0.045	0.091
B9	0.045	0.136	0.136	0.091	0.091	0.045	0.091	0.091	0.000	0.045	0.091	0.091
B10	0.045	0.091	0.091	0.136	0.091	0.045	0.091	0.091	0.091	0.000	0.045	0.091
B11	0.045	0.136	0.091	0.045	0.045	0.045	0.091	0.091	0.091	0.091	0.000	0.136
B12	0.091	0.136	0.136	0.045	0.045	0.045	0.091	0.045	0.136	0.091	0.136	0.000

Table 8. Total influence matrix.

Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	Row Total (D-Values)
B1	0.643	1.345	1.270	0.938	0.916	0.791	1.029	0.950	1.183	0.945	0.956	0.986	11.952
B2	0.742	1.371	1.411	1.055	0.987	0.890	1.193	0.990	1.280	1.020	1.029	1.025	12.991
B3	0.701	1.410	1.215	0.998	0.932	0.767	1.090	0.970	1.247	0.926	0.938	0.999	12.191
B4	0.769	1.433	1.355	0.964	0.935	0.798	1.137	1.056	1.261	1.049	1.013	1.010	12.781
B5	0.603	1.102	1.003	0.763	0.673	0.658	0.840	0.745	0.970	0.741	0.790	0.774	9.661
B6	0.569	1.112	1.051	0.771	0.761	0.578	0.886	0.749	0.944	0.747	0.757	0.817	9.742
B7	0.763	1.539	1.458	1.091	0.977	0.835	1.108	1.060	1.359	1.052	1.062	1.094	13.399
B8	0.761	1.524	1.443	1.121	1.008	0.831	1.181	0.969	1.311	1.046	1.016	1.081	13.291
B9	0.729	1.467	1.388	1.036	0.968	0.798	1.134	1.009	1.175	0.965	1.014	1.041	12.723
B10	0.701	1.367	1.292	1.035	0.928	0.762	1.086	0.971	1.205	0.882	0.934	0.997	12.159

Table 8. *Cont.*

Barriers	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	Row Total (D-Values)
B11	0.705	1.423	1.311	0.968	0.899	0.772	1.101	0.976	1.220	0.974	0.901	1.050	12.300
B12	0.798	1.531	1.448	1.042	0.971	0.833	1.184	1.014	1.352	1.045	1.096	1.008	13.323
Column total (R values)	8.483	16.624	15.646	11.781	10.954	9.312	12.967	11.460	14.509	11.391	11.504	11.882	146.513

Table 9. Degree of influence.

Barriers	Row Total (D)	Column Total (R)	D+R Values	D−R Values
B1	11.952	8.483	20.435	3.468
B2	12.991	16.624	29.616	−3.633
B3	12.191	15.646	27.837	−3.455
B4	12.781	11.781	24.562	1.000
B5	9.661	10.954	20.615	−1.292
B6	9.742	9.312	19.055	0.430
B7	13.399	12.967	26.366	0.432
B8	13.291	11.460	24.751	1.832
B9	12.723	14.509	27.231	−1.786
B10	12.159	11.391	23.550	0.768
B11	12.300	11.504	23.804	0.796
B12	13.323	11.882	25.205	1.441

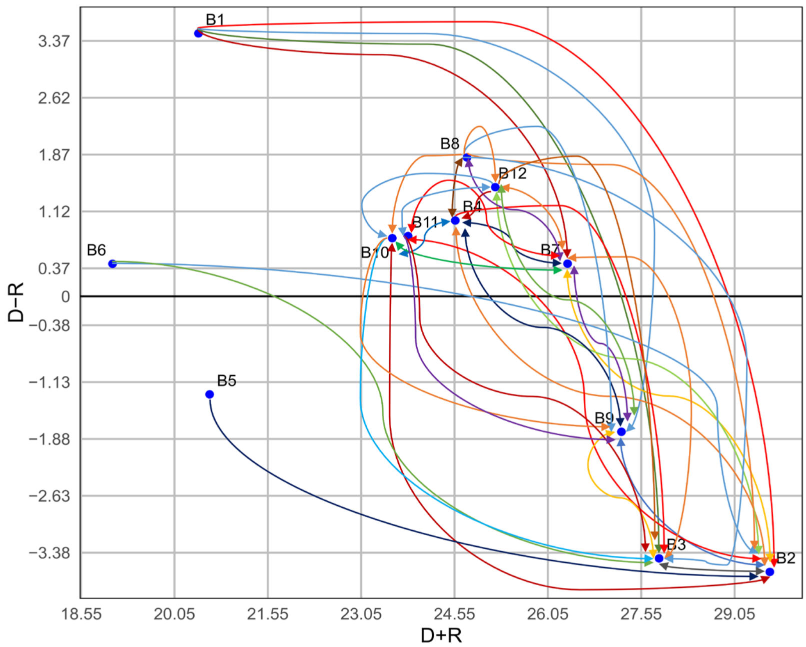

Figure 3. DEMATEL causal diagram.

5. Findings and Discussion

The original aim of the ISM model was to acquire a hierarchy of levels for barriers to IoT adoption in HL, which would provide practitioners in the HL field with information regarding the dependency relationships between IoT barriers. This information would aid in overcoming obstacles in implementing the technology in HL by concentrating on the critical adoption barriers. The results of this study are noteworthy as they reveal six distinct hierarchical levels that describe the relationships among the identified IoT barriers. At the top of this hierarchy, legal and regulatory challenges (B10) emerged as the most influential factor in IoT adoption in HL. This factor encompasses a variety of legal and regulatory aspects including, but not limited to, laws and regulations concerning data privacy, standards for IoT device operation, and rules regarding the use of technology across different regions or jurisdictions. Its position at the top level of the hierarchy implies its significance and how it is affected by the cumulative effects of all the other barriers situated beneath it in the hierarchy. This indicates that to successfully integrate IoT into HL, regulatory and legal issues need to be addressed comprehensively. This could potentially trigger a cascading effect, easing other barriers down the hierarchy.

On the second level of the hierarchy are two key barriers: lack of power (B6) and lack of standardization (B7). Lack of power, in this context, refers specifically to the availability of electricity, which is essential for the operation of any IoT device. In many humanitarian contexts, consistent access to reliable power sources can be a significant challenge, and without it, the deployment of IoT devices could be severely restricted. Lack of standardization (B7) refers to the absence of common protocols or interfaces, which results in interoperability issues between different IoT systems and devices. Without standardization, the effectiveness of IoT devices could be compromised due to communication difficulties between them. The placement of these two barriers at the second level suggests that they are influenced by all the barriers at the lower levels. Simultaneously, they significantly impact the highest barrier—legal and regulatory challenges (B10). These barriers' interplay highlights the multifaceted nature of the challenges involved in IoT adoption in HL, emphasizing the need for a comprehensive strategy that addresses these barriers not individually but as part of an interdependent system to promote greater IoT adoption in the field of HL.

At the third level, we have a relatively dense cluster of six barriers, all of which interact with each other in a reciprocal manner. These barriers include interoperability (B3), network availability (B5), cost (B1), technical complexity (B2), data privacy and security (B4), and organizational resistance (B12). The complexity of this level signifies the intricacy of IoT adoption in HL, with many moving parts interwoven and influencing one another. However, a unique dynamic emerges beneath this complex level. Three critical barriers—data quality and accuracy (B8), integration with existing systems (B9), and human capacity (B11)—reside in the subsequent levels. These barriers are distinctive as they hold the most substantial driving power among all identified barriers. That is, they have the greatest influence over all other barriers in the system.

Data quality and accuracy (B8) reflect the fundamental need for reliable and precise information in IoT systems. Poor quality or inaccurate data could drastically undermine the effectiveness of these systems. Integration with existing systems (B9) underscores the challenge of incorporating new IoT solutions into established HL infrastructures and processes. Lastly, human capacity (B11) points to the skills, training, and expertise required to implement and maintain IoT systems effectively. These three barriers, given their driving power, are instrumental in the adoption of IoT in the HL field. Addressing these barriers could potentially trigger a domino effect, easing the other barriers and thereby smoothing the path for more effective and widespread adoption of IoT in HL. Their strategic importance cannot be overstated, as improvements in these areas would likely reverberate through the entire hierarchy, potentially lightening the challenges associated with the other barriers.

The MICMAC analysis, used to discern the dependencies among the twelve identified barriers to IoT adoption in HL, segregates the barriers into three distinct clusters. When comparing these clusters, each presents a unique set of characteristics, representing different degrees of interaction and influence over the IoT adoption process in the HL field. Interestingly, the first cluster, termed autonomous barriers, remains empty, signifying that none of the barriers operate in isolation. This unique finding underscores the complexity of IoT adoption in the HL field. It tells us that all the barriers are intricately connected, making their impact and influence on the adoption process more pervasive. When viewed in this light, it becomes evident that any intervention to facilitate IoT adoption in the field of HL must be holistic, taking into account the interconnected nature of these barriers. Next, Cluster II, referred to as dependent barriers, is characterized by barriers with high dependence power and low driving power. These barriers, namely lack of power (B6), lack of standardization (B7), and legal and regulatory challenges (B10), hold a significant position in the adoption process. Comparatively, they are more dependent on the influence of other barriers and carry considerable weight due to their high impact on IoT adoption in HL. Due to their dependency, they require high-priority attention and support from the HL practitioners and managers, to reduce their effect on the IoT adoption process.

Cluster III, or linkage barriers, includes barriers with both high dependence power and high driving power. This combination renders them as sensitive factors that can induce ripple effects in the system when altered. The barriers in this cluster, including cost (B1), technical complexity (B2), interoperability (B3), data privacy and security (B4), network availability (B5), and organizational resistance (B12), are volatile due to their high influence on and __dependence from other barriers. Thus, when addressing these barriers, it becomes vital to be cognizant of their sensitivity and potential to create significant ripple effects that can impact the entire system. Finally, we have Cluster IV, the driving barriers. These barriers, characterized by low dependence power and high driving power, exert a high level of influence on the entire system. This cluster includes data quality and accuracy (B8), integration with existing systems (B9), and human capacity (B11). They are positioned in a way that they can shape the behavior of all other barriers across all hierarchical levels. As such, they demand meticulous handling from HL managers. Any changes to these barriers are likely to lead to pervasive effects on all other barriers, making them a critical focus point in efforts to increase the adoption of IoT in the HL field.

The ISM approach, despite offering valuable insights into the hierarchical relationships and interdependencies among the barriers to IoT adoption in HL, does not provide a quantitative measure of the extent of influence between these barriers. To address this gap, we employed the DEMATEL technique, which is a quantitative method that offers a more granular perspective by measuring the extent of the interactive effects among the barriers. By applying the D+R and D-R values extracted from the DEMATEL method, we can distinctively classify the barriers into 'cause' and 'effect' categories. This vital distinction allows us to understand which barriers primarily exert influence ('cause'), and separate them from those predominantly influenced by others ('effect') in the complex process of IoT adoption in HL.

In this comparative analysis, 'technical complexity' (B2) surfaced as the most influential barrier, demonstrating the highest D+R value among all barriers. This elevated value signifies a broad influence over the other barriers, positioning technical complexity as a cardinal driving factor in shaping the landscape of barriers in HL's IoT adoption. Interpreting the implications of technical complexity requires comprehension of its multi-faceted nature in the IoT context. The inherent complexity encompasses intricate system integration demands, the need for specialized technical skills, and challenges in managing diverse IoT devices, which all contribute to the 'technical complexity' barrier. However, this complexity does not function in isolation. It significantly influences other barriers. For instance, the heightened energy requirements associated with technically complex operations could worsen the 'lack of power' problem (B6). Likewise, the intricacies involved in regulating sophisticated technologies could intensify the 'legal and regulatory challenges' (B10).

When interpreting the interconnected nature of these barriers, it is clear that any strategy aimed at overcoming the barriers to IoT adoption in HL should prioritize addressing 'technical complexity' (B2). By mitigating this key barrier, HL managers could potentially reduce the impact of several other barriers due to its central influential role. This understanding underscores the necessity of a comprehensive understanding of both the individual barriers and the interconnected web they form, which will help to effectively navigate the path towards successful IoT adoption in HL.

Another comparative analysis of the D-R values reveals that the barriers cost (B1) and lack of power (B6) emerge as significant net causes within the system. These barriers do not merely exist as individual challenges; rather, they exert considerable influence over the other barriers in the adoption of IoT in HL. The high cost of IoT implementation (B1), including investment in hardware, software, training, and maintenance, can undoubtedly be a deterrent for many organizations. This barrier could further influence other barriers, such as 'technical complexity' (B2), 'lack of standardization' (B7), and 'integration with existing systems' (B9), due to the inherent financial constraints associated with addressing these issues. Similarly, lack of power (B6), a substantial issue in many regions where HL operations are critical, could exacerbate 'network availability' (B5) and 'data quality and accuracy' (B8) barriers, given that both network and data operations are significantly dependent on reliable power supply.

On the receiving end, addressing the 'cost' and 'lack of power' barriers promptly could prompt a cascading effect of reducing the influence on other barriers, potentially simplifying the path to IoT adoption. Organizations may be more willing and capable of adopting IoT in their operations, leading to improvements in the management and efficiency of HL. This adoption can subsequently contribute to quicker response times and a more effective deployment of resources, thereby enhancing the overall performance and impact of HL operations.

Research Implications

In the HL context, organizations are facing increasing pressure to respond quickly and effectively to natural disasters, conflicts, and other humanitarian crises. The adoption of new technologies, such as IoT, can help organizations better understand and manage their operations, from supply chain management to disaster response. However, these technologies require significant investments in terms of technology, human resources, and financial capital. Embracing IoT can provide organizations with real-time data and insights, enabling them to make informed decisions and respond more effectively to crises. As data-centric approaches to HL are anticipated to become increasingly essential, humanitarian organizations may struggle to keep up with their peers if they fail to adopt IoT. In this study, we investigate the barriers to IoT adoption in HL using ISM and DEMATEL approaches. The results indicate that legal and regulatory challenges are significant barriers to IoT adoption in HL. Specifically, there are no clear regulations and guidelines surrounding the deployment of IoT in HL. Unlike in other industries, such as retail or manufacturing [36], where there may be more established legal and regulatory frameworks in place, IoT use in HL is still in its nascent stages [65], and there are few established guidelines governing its implementation. This lack of clarity can lead to uncertainty and hesitation among HL managers who may be concerned about potential legal and ethical issues that could arise from IoT in humanitarian contexts [72,100,123]. For example, several questions related to data privacy and security or concerns around the use of the technology in HL settings can arise. In addition, the absence of clear guidelines can also make it challenging for HL managers to make informed decisions around the implementation of IoT systems because they may not know what best practices to follow and what legal requirements to comply with. To address these challenges and harness the full potential of IoT, it is crucial for HL managers and practitioners to engage in active dialogue with regulatory bodies to advocate for the establishment of clear, pragmatic guidelines and standards for IoT implementation in humanitarian settings. This collaborative approach can facilitate a smoother adoption process, ensuring that IoT technologies are leveraged effectively to enhance operational efficiency and improve disaster response outcomes.

Furthermore, it is important for regulatory bodies and other HL stakeholders to collaborate to establish clear guidelines and regulations around IoT use in HL. This could involve developing standards and best practices for data privacy and security, as well as guidelines for the appropriate use of the technology in HL. In the case of IoT devices to monitor and track the distribution of emergency supplies, there are no standardized protocols or frameworks for data collection, analysis, and sharing. If one humanitarian organization uses data collection protocols that are different to those applied by another organization, it can be challenging to integrate the data and achieve a comprehensive understanding of the humanitarian supply chain. Additionally, the absence of standardized frameworks can result in data inconsistencies or quality issues, which can lead to delays or mistakes in the delivery of aid and relief supplies. Practically, HL organizations should prioritize interoperability and standardization in their IoT initiatives, potentially through sector-wide collaborations, to ensure that data and system compatibilities are addressed from the outset. This strategic focus not only aids in operational coordination but also enhances the collective efficacy of humanitarian responses. Another area where regulations are lacking is the use of IoT-enabled devices and sensors in disaster response and management. For instance, there is currently no clear guidance on how to use IoT data to predict and mitigate the impact of natural disasters or how to manage the influx of data generated by multiple devices during a crisis. As a result, by establishing supportive regulations and clear guidance for managers, it may be possible to overcome some of the hesitation and uncertainty around IoT implementation and encourage more widespread adoption of the technologies in HL.

One of the significant results of this study is that interoperability, lack of standardization, and integration with existing systems are influenced by legal and regulatory challenges. For managers in the HL sector, addressing these challenges head-on by collaborating with technology providers and regulatory agencies can pave the way for creating more cohesive and interoperable IoT ecosystems. Such proactive management practices are essential for enhancing the resilience and responsiveness of humanitarian operations to global crises. In the realm of interoperability, legal and regulatory challenges are more pronounced, as IoT devices from different manufacturers and vendors may not be compatible with another one or with existing systems [91,92]. As a result, this can make it difficult to achieve interoperability between devices from different disaster-stricken regions or between devices that were designed to meet different regulatory requirements. Similarly, regulations related to data and privacy can impact interoperability. For example, regulations may require certain levels of data encryption or access control for IoT devices, thereby creating compatibility issues with other devices that do not meet those requirements. Since aid agencies and relief organizations can rely on different IoT devices and systems to monitor and track the distribution of emergency supplies (e.g., food, water, medicine, medical equipment, etc.), the lack of interoperability can hinder the integration of these devices and systems into a cohesive network, leading to duplication of efforts, and also contributing to inefficiencies and delays in the delivery of aid [23].

Besides interoperability, lack of standardization is influenced by legal and regulatory challenges. One example of how regulations can hinder standardization is the requirement for different data collection and reporting standards in different countries or regions [86]. Inconsistencies in data collection and reporting can lead to difficulties in comparing and analyzing data across different HL systems, thus affecting decision-making in relief operations. This can be particularly problematic in the context of cross-border aid delivery, where different countries have different regulations and data collection requirements. Furthermore, the lack of a unified legal framework for IoT devices can affect standardization. Without clear and comprehensive legal frameworks, there may be differences in the way IoT devices are manufactured and used, leading to divergences in standards and interoperability. Thus, a fragmented IoT landscape can make it challenging to develop and implement standardized IoT systems in HL. As regulations around the use and adoption of IoT technologies in certain disaster or conflict zones may not be available, it is difficult to establish standard operating procedures for IoT use in these contexts. Finally, legal and regulatory factors are significant barriers to the integration of IoT devices and systems with existing HL and management software, supply chain management systems, and communication networks in HL. In order to address this issue, regulations should be put in place to ensure that IoT devices are manufactured according to common standards and specifications, which would help to facilitate integration between different HL systems [23].

6. Conclusions, Limitations, and Future Research

The integration of IoT into the domain of HL presents a wealth of possibilities for improved supply chain visibility and optimized aid distribution, thereby magnifying the effectiveness of humanitarian efforts. The present study has meticulously identified and critically analyzed a dozen barriers to the adoption of IoT in the HL arena, further stratifying them based on their driving and dependence powers using the ISM method. A subsequent application of the DEMATEL technique enabled the classification of these barriers into causal or resultant groups, enriching our understanding of their interrelationships and implications for HL managers. Our findings suggest that key causal barriers—including lack of standardization (B7), organizational resistance (B12), data quality and accuracy (B8), and legal and regulatory challenges (B10)—warrant significant attention from HL practitioners. Addressing these barriers is deemed more impactful than concentrating on the primary effect barriers, such as technical complexity (B2), interoperability (B3), and integration with existing systems (B9).

Our study's conclusions prompt us to present strategic recommendations that primarily aim at attenuating the cause barriers identified. These barriers significantly impact IoT adoption in HL, thereby necessitating concerted and targeted efforts to resolve them effectively. Firstly, we recommend the establishment and implementation of standardized protocols for IoT devices. Interoperability, or the ability of different IoT systems and devices to work seamlessly together, is crucial to the successful deployment of IoT in the HL field. However, the lack of standardization (B7) is a prominent barrier that impedes this interoperability, leading to technical complexities that can stunt the effectiveness of IoT. Therefore, HL managers should prioritize efforts towards developing and promoting the use of universal protocols that enable disparate IoT devices to communicate and operate effectively within a unified system. This could involve collaborating with IoT vendors, technology experts, and other relevant stakeholders to create and adopt these standards. Secondly, organizational resistance (B12) stands as a substantial barrier to IoT adoption. This resistance often stems from a lack of understanding about IoT's benefits, fear of change, and concerns about the potential disruptions that the adoption of new technology might cause. Therefore, HL managers should proactively manage this resistance by engaging in continuous communication and training. They could clarify the benefits of IoT adoption, provide adequate training to build the necessary skills, and involve employees in the adoption process to encourage buy-in and reduce resistance. Thirdly, the quality and accuracy of data (B8) are essential to leveraging the full potential of IoT. Erroneous or low-quality data can lead to incorrect decision-making, reducing the overall effectiveness of HL operations. Hence, it is crucial for HL managers to put in place robust data management practices that ensure the reliability, accuracy, and timeliness of the data generated by IoT devices. This could involve deploying advanced data validation and cleaning techniques, investing in data quality tools, and training staff on the importance of data accuracy. Finally, we recommend active engagement with regulatory bodies to shape a favorable legal framework for IoT adoption. Legal and regulatory challenges (B10) can create an environment of uncertainty that inhibits HL stakeholders from investing in IoT. To overcome this barrier, HL managers should actively participate in discussions and advocacy efforts with regulatory authorities to develop clear, comprehensive, and supportive legal frameworks that facilitate IoT adoption. This could involve educating policymakers about the benefits and challenges of IoT, lobbying for supportive regulations, and partnering with legal experts to ensure compliance with existing laws while pushing for necessary reforms. In summary, tackling these cause barriers through the development of standardized protocols, proactive management of organizational resistance, improvement of data quality and accuracy, and active engagement with regulatory bodies can significantly enhance the prospects for successful IoT adoption in HL.

Despite the valuable insights obtained from this preliminary study, several limitations should be considered when interpreting the findings. Firstly, this study is limited to a single case study and may not be representative of the broader HL context. Future research could explore the barriers to IoT adoption across different disaster scenarios and geographical locations to provide a more comprehensive understanding of the issues faced by HL managers. Secondly, the weights used in the ISM and DEMATEL models were based on the judgments of experts from the HL field, which may be biased and subject to personal interpretations. Future research could rely on a larger sample size or conduct empirical surveys to obtain more accurate weights and validate the identified relationships between IoT barriers. Moving forward, several future research directions can be explored in the field of IoT applications in HL. Firstly, scholars could examine the potential benefits and limitations of integrating IoT solutions with other emerging technologies, such as AI, blockchain technology, and machine learning, to improve the efficiency and effectiveness of disaster relief operations [124–128]. Secondly, future research opportunities include investigating the impact of cultural and social factors on the adoption of IoT in different HL contexts, as these factors can significantly impact the acceptance and deployment of new technologies. Thirdly, the study identified the lack of standardization as a critical barrier to IoT adoption in HL. Accordingly, future studies could explore the development of standardized protocols and frameworks for IoT systems to improve interoperability and reduce technical complexities in HL. Finally, researchers could also investigate the ethical and social implications of IoT adoption in HL, including issues associated with data security, privacy, and accountability. Addressing these research gaps will offer valuable insights and contribute to the development of effective strategies for the effective adoption and implementation of IoT in HL.

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