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Research article

Sustainable medical waste management through blockchain technology and big data: A structural analysis and modeling of barriers using the ISM-MICMAC and AHP approach

Muhammad Ismail[1], Zhongdong Xiao[1], Abdul Waheed[2,*], Asifa Iqbal[3], El-Sayed M. El-Kenawy[4,5], Amel Ali Alhussan[6], Marwa M.Eid[7,8] and Doaa Sami Khafaga[9]

1 School of Management, Xi'an Jiaotong University, Xi'an, 710049, China
2 School of Business, Xian International University, Xian, China
3 School of International Studies, Zhengzhou University, China
4 Delta Higher Institute of Engineering and Technology, Department for Communication and Electronics, Mansoura 35511, Egypt
5 Applied Science Research Center, Applied Science Private University, Amman, Jordan
6 Department of Computer Sciences, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia
7 Faculty of Artificial Intelligence, Delta University of Science and Technology, Mansoura, Egypt
8 Jadara Research Center, Jadara University, 21110, Jordan
9 Department of Computer Sciences, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia

* **Correspondence:** Email: XAIU24250@xaiu.edu.cn.

Abstract: Due to the COVID-19 pandemic, every country faces numerous issues, and seemingly inadequate treatment of medical waste (MW) is one of them. If proper measurements are not taken about MW, then it will have hazardous effects on the environment and nature. In this study, we identified significant barriers to integrating blockchain (BC) and big data (BD) to manage MW and analyze their interrelationship effectively. This study was designed in three parts: Identifying barriers through a literature review, past studies, and expert judgments; and analyzing barriers and their impact using a hybrid approach, including Interpretive Structural Modeling (ISM), MICMAC, and the Analytic Hierarchy Process (AHP). In this study, 10 factors were mined from the literature review, and five were taken from experts' opinions, which influenced the adoption of BC and BD for managing medical waste management (MWM) in metropolitan city hospitals. The results from ISM-MICMAC indicated that the key barriers were: Insufficient resources, lack of management rules and policies, lack of technical infrastructures, and lack of skilled workforce. These were more most formidable challenges for the adoption of BDBC-MWM in the Pakistan medical industry, and the same as the results from AHP showed that the significant barriers and most formidable challenge for the adoption of BDBC-MWM were: Lack of research and development units, lack of training and education of staff, lack of management support, lack of rules, regulations, and policies, lack of international cooperation, and inadequate technological infrastructure.

Keywords: big data; blockchain; medical waste management; ISM; MICMAC; AHP; barriers; metropolitan cities
Mathematics Subject Classification: 90C26, 90C29, 90C30

1. Introduction

Urbanization is a consistent feature of global demography [1], with millions of people migrating from rural areas to urbanized regions [1]. According to Habitat [2], urbanization in developing countries, such as those in Africa, Asia, and Latin America, has contributed to an increase of over 20 million people through a population boom. In the next decade, China and India are projected to have as many as one-third of their populations in urban areas [3]. The acceleration of urbanization, which contributes to economic growth and social development, brings heavy burdens, including a substantial amount of waste [1]. Fast urbanization, industrialization, and economic development in megacities lead to the production of vast amounts of waste material, such as medical waste (MW), electrical and electronic equipment waste (e-waste), plastic waste, and municipal solid waste [4], shown in Figure 1, sourced by Singh, Ogunseitan [5]. This generation of waste has been categorized into several classifications, such as MW, electrical and electronic waste, plastic waste, and solid waste [6]. Of the latter, MW is highly dangerous, and its management and disposal are unique. Inadequate handling and management of MW are associated with environmental pollution and serious health hazards, especially in developing countries where there is poor waste management practice. MW is a highly hazardous waste that contains sharps, radioactive substances, blood-soaked cotton, and chemical waste, posing limited public health hazards [7]. Poor medical waste management (MWM) in hospitals is therefore one of the causes for the transmission of diseases such as AIDS, Hepatitis B, and Hepatitis C, and the World Organization and Press (1999, 2014) have estimated that inadequate disposal of MW can be attributed to millions of infections worldwide, which is an indication of improved waste management [8].

The target should be to reach 15−20% of total medical and healthcare waste from medical facilities. Still, the practice of such a component ratio could be extended to 100% due to improper and insufficient implementation of MWM practices [8]. Inadequate and unsuitable MWM practices at hospitals can affect human health, the community, and environmental conditions [9,10]. In this context, proper and technical handling and segregation of MW is essential because issues arise from mishandling of medical waste by sharp instruments, dangerous chemicals, diseases transmitted to other people from infectious persons, and polluted environmental conditions by toxic substances [11]. In a report published by the United Nations World Health Organization (WHO), MW mishandling and improper disposal have been linked to more than two million AIDS cases, 2 million cases of Hepatitis

C, and 21 million cases of Hepatitis B [11]. Different types of MW and their forms, such as general waste (67%), infectious waste (27%), and sharp waste (4%), are the major contributors in this regard. The above facts reveal the necessary, appropriate handling and segregation of medical waste [12]. In the global scenario of economic development and commercial activities, the effective treatment of MW is a significant and crucial matter for the world [13]. The leveraging of blockchain (BC) and big data (BD) is a practical approach for addressing and mitigating the issues mentioned above [14]. Through the integration of these technologies, innovative methods are facilitated to minimize costs, enhance tracing, simplify relationships with intermediaries, and fulfill the expectations of different stakeholders in the healthcare ecosystem [11,15,16]. BD enables effective data collection, analysis, and sharing, which can result in improved monitoring and MMW practices among stakeholders, including health protection agencies, government bodies, and hospitals. Additionally, BC ensures accountability and provides real-time tracking of waste through transparent, immutable records. The leveraging of the BD and BC can enhance the process of monitoring MW disposal, thereby avoiding detrimental environmental effects and ensuring that appropriate guidelines are observed [11,15,17,18]. Such technological synergy can help reinforce more sustainable, secure, and efficient management practices throughout the medical waste lifecycle, from generation to disposal.

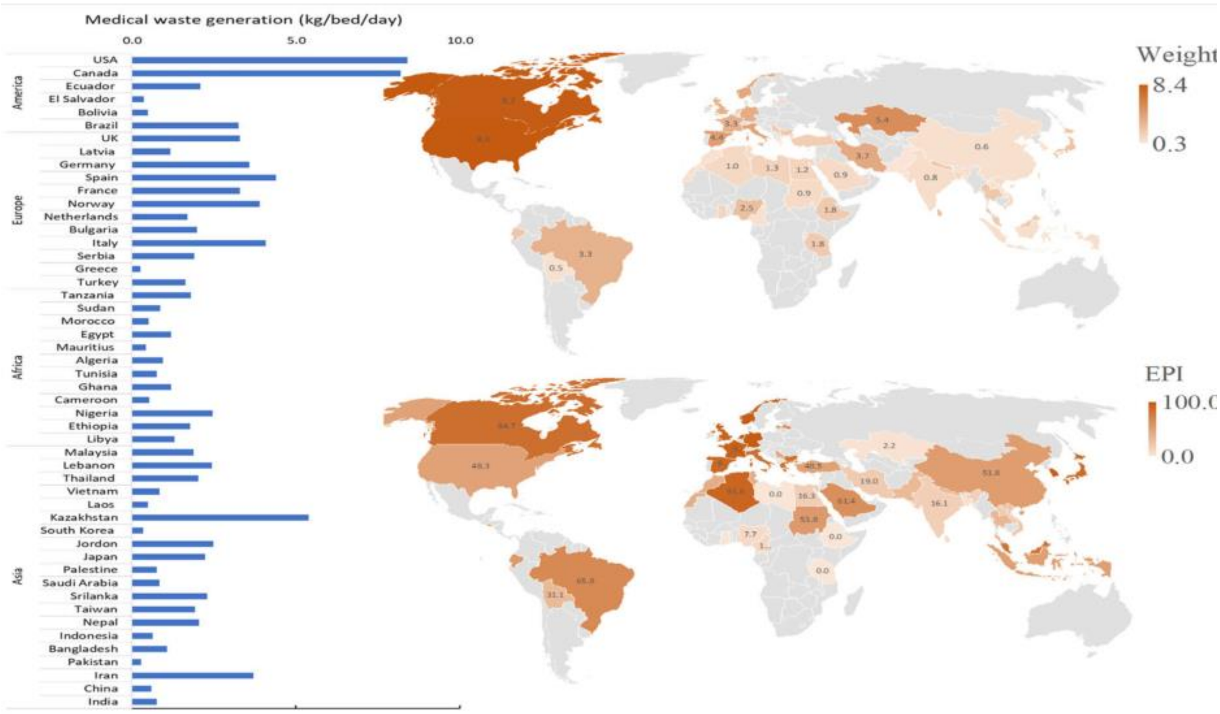

Figure 1. Sourced by Singh, Ogunseitan [5].

In the past, several studies have been conducted on MWM in different countries. Komilis, Fouki [19] worked on medical waste barriers and challenges in Greece. Nguyen, Bui [20] examined the medical solid waste in Vietnam. According to Emamjomeh [21], an Iranian perspective on the management of medical solid waste has been written, and several studies have been conducted on various aspects of waste management systems, including segregation, transportation, hygiene, storage, sanitation, training, and collection [21−29]. Previous research efforts have focused on addressing the constraints of MWM in terms of physical infrastructure and manual processes, while giving scant consideration to emerging technologies that could redefine the field. We need this research because traditional methods have shortcomings, and there is a lack of literature on how BD and BC technologies can be integrated to improve MWM in metropolitan hospitals, especially in developing countries. These measures will go some way toward overcoming several issues, including waste inefficiencies, poor traceability of waste handling and disposal activities, and non-compliance with environmental regulations, among others.

Our objective of this study is to propose and investigate the application of BC and BD in MW management (BDBC-MWM) to assess how these technologies can be utilized to enhance MW management in metropolitan hospitals. The originality of the work stems from the fact that BD and BC are employed in MWM, which is an under-addressed issue, especially in developing countries. Although these technologies have been extensively reported on in other areas, there is limited discussion about their application for MW destination and treatment, particularly in the developing world during rapid urbanization [14]. BC enables a transparent and decentralized system to monitor the process of medical waste from creation to disposal, ensuring that all links in the chain can be accounted for [16,17]. BD, in turn, can facilitate real-time monitoring and decision-making to optimize resource allocation and enforcement of regulations [16]. We are motivated by the pressing need to update MWM traditions to address the growing urbanization of cities and the increasing volume of medical waste in city hospitals. The combined use of BC and BD has the potential to provide a solution to these risks by increasing efficiency in MW while supporting compliance with environmental and health laws. By examining the integration of the two technologies, this paper aims to address the shortcomings and develop a more efficient, scalable, and sustainable alternative to traditional MWM systems.

The following objectives of the study have been formulated for this work:

- To trace the key barriers and reckon the adoption of BDBC-MWM among metropolitan hospitals based in developing countries.
- To consider how BC and BD might enhance MWM practices, with a focus on transparency, accountability, and resource efficiency and optimization.
- To propose a hybrid methodological approach, integrating ISM-MICMAC with AHP to evaluate the implementation and impact of BDBC-MWM.

This paper contributes to the literature by offering a novel perspective on incorporating BD and BC for MWM, which is particularly applicable to large hospitals in metropolitan areas of developing nations. In contrast to previous research on classical MWM, we examine the impact of technological innovation on waste treatment management. Finally, this study offers valuable insights for public health and environmental sustainability implications to hospital administrators, policymakers, and healthcare agencies in breaking down the barriers towards BDBC-MWM adoption. The remainder of the paper is organized as follows: In Section 2, we present a literature review on conventional MWM models and BD and BC applications for managing medical waste. In Section 3, we explain the research methodology, including ISM-MICMAC and AHP techniques, applied to evaluate the adoption of BDBC-MWM. In Sections 4 and 5, we present results and discuss the challenges and benefits of applying BD and BC technologies in MW treatment. In Section 6, we conclude the study with recommendations for practice and future research.

2. Literature review

Several studies have been conducted on BD, BC, and MWM challenges and obstacles from various approaches and perspectives. In this study, we select only the barriers that have a direct impact on the sustainability of the MWM system in megacities. Based on the results in Table 1, we chose to focus on the key constraints. Lack of training and workshops was found in BD, BC, and MWM in these studies [10,30,31]. The gap prevents the effective use of BD and BC, as innovations required to ensure operational efficiency in MWM were critical. Inadequate technological infrastructure, as reported in various research studies [31−34], hinders organizations from fully adopting BD and BC technologies, which are resource-intensive and require advanced infrastructure for efficient operation. Insufficient resources, a common problem identified in the literature [33−35], limit the appropriation of sufficient financial and human resources for incorporating BD and BC into systems for managing MW. According to several researchers [10,33,36], a lack of skilled IT personnel is another major challenge, as the necessary technical know-how to operate and run these technologies is usually inadequate in the medical waste sector. Insufficient information and knowledge & awareness regarding BDBC-MWM are found to be critical hindrances [33,34,36−38], impeding stakeholders' complete understanding of the advantages and prospects related to BD and BC for MWM. The lack of rules, regulations, and policies, as also noted by Farooque, Jain [34], and Bag, Viktorovich [32], constrains the legal facilitation of transactions of BC and BD techniques in MWM, where they suffer from a lack of legal support in their application. Lack of management support is also a significant barrier, as hospital and healthcare center managers are often hesitant to provide the resources required for technological changes without understanding their value [30,33,35]. Data security issues have also been one of the common challenges for the adoption of BC and BD in managing MW [31,35,36], as sensitive patient and waste data need to be kept secure during storage and transfer. Personnel incompetency, as observed in the MWM studies [31,33], underscores the importance of having experienced manpower to handle and guide people in implementing these technologies. The absence of research and development units does not enable effective and innovative solution processes for integrating BD and BC into MWM procedures [10,30,37]. Lack of industry involvement and collaboration is also identified as one of the barriers by multiple studies [33,35]. Partnership with technology providers, regulatory authorities, and other industry stakeholders should be inherent in taking BDBC-MWM to the next level of adoption. Several obstacles may hinder the scalability of BD and BC applications in MWM, including a lack of industrial internet and inadequate international cooperation due to barriers [32,35]. Finally, the inability to learn from advanced nations restricts access for developing nations to global knowledge in MWM [39]. It slows the dissemination of best practices from most developed healthcare systems.

Numerous researchers have discussed the adoption of BD and BC technologies within MWM, often emphasizing how these technologies can enhance data sharing, privacy preservation, traceability, and environmental sustainability. Attaran [40] and Chen, Dou [41] highlighted the benefits of BD in improving operational efficiency, while BC ensures data security and transparency in waste monitoring. These technologies, combined, provide a secure and accountable way to manage medical waste, which is essential for the sustainability of the healthcare industry. However, researchers have concentrated on only individual aspects of BD, BC, and MWM, and there is no integrated platform for MWM. In an attempt to fill this gap, we investigate in this work how the synergic adoption of BC and BD may bypass the hindrances found in Table 1. Connectivity and integration will enable hospitals and health facilities to address data security risks, fulfill regulatory compliance requirements, and maximize operational efficiency, thereby contributing directly to the sustainability of MWM practices. To identify and select the core barriers that influence the sustainability of BDBC-MWM in metropolitan cities, we also concentrate on achieving four evaluation criteria (shown in Table 8) to further clarify their related obstacles. The four criteria are: Government Barriers, Human Barriers, Economic & Organizational Barriers, and Technological Barriers. These key factors are chosen due to their significant impact on MWM systems and the possibility of addressing challenges associated with BD and BC adoption. Government barriers are included because policy frameworks and legal backgrounds could impact whether BDBC-MWM is implemented. Barriers such as the lack of research and development units, lack of international cooperation, lack of rules, regulations, and policies, lack of industry involvement and collaboration, and lack of learning from advanced nations have been identified in determining how these technologies can successfully be incorporated into health systems [10,33,42]. It requires supportive public policies to implement the requisite infrastructure, resources, and partnerships. The selection of Human Barriers was motivated by their influence on the success of enacting BD and BC in MWM. The insufficient training and workshops, lack of training and workshops, lack of skilled IT personnel, and inadequate staff capability hinder the effective applicability of these technologies in the health system [10,36]. These human factors also underscore the importance of workforce training and education in the adoption of advanced technology.

Economic and Organizational Barriers are chosen to identify factors that are important in facilitating the availability of required resources and managerial support for adopting BD and BC in the MW disposal chain. Lack of management support, insufficient resources, and a lack of knowledge about BDBC-MWM are also the major barriers to allocating sufficient resources to accept and sustain these technologies in healthcare facilities [33,35]. Furthermore, the lack of industry involvement and the absence of industrial internet are also significant, as they impede collaboration in developing the technical infrastructure required for these applications [35]. Finally, Technological Barriers are also perceived as in place, given the essential involvement of technological infrastructure in the implementation of BD and BC solutions in MWM. Inadequate technological infrastructure, lack of information, and data security issues are the three major technical barriers to the complete application of these technologies [37,42]. Securely tracking and sharing information regarding medical waste is critical to compliance and sustainability. The above four chosen criteria are directly relevant to the challenges and opportunities in integrating BD and BC technologies into an MWM system. The focus on government, human, economic, and technological barriers in this study presents a comprehensive picture of the essential obstacles that health organizations encounter when adopting and using new technologies. The recognition of these barriers, which is demonstrated in Table 8, provides the basis for developing approaches to address these difficulties and establish a more sustainable medical waste treatment system.

Table 1. Identification of barriers from past studies.

#	Barrier Name	Variables	[10]	[30]	[43]	[33]	[35]	[36]	[44]	[45]	[46]	[7]	[47]	[37]	[48]	[42]	[49]	[38]	[32]
1	Lack of training and workshops	BD		✓												✓			✓
		BC			✓	✓													
		MWM	✓								✓								
2	Inadequate technological infrastructure	BD		✓												✓			✓
		BC			✓		✓		✓										
		MWM								✓	✓								
3	Insufficient resources	BD		✓												✓			✓
		BC				✓	✓												
		MWM	✓							✓	✓								
4	Lack of skilled IT personnel	BD		✓												✓			✓
		BC					✓	✓	✓										
		MWM	✓							✓	✓								
5	Insufficient information	BD														✓			✓
		BC							✓										
		MWM								✓	✓								
6	Insufficient knowledge & awareness regarding BDBC-MWM	BD														✓			
		BC				✓	✓		✓										
		MWM											✓						
7	Lack of rules, regulations and policies	BD		✓															✓
		BC				✓	✓	✓											
		MWM								✓									

Continued on next page

#	Barrier Name	Variables	[10]	[30]	[43]	[33]	[35]	[36]	[44]	[45]	[46]	[7]	[47]	[37]	[48]	[42]	[49]	[38]	[32]
8	Lack of Management support	BD														✓			✓
		BC				✓	✓												
		MWM	✓																
9	Data security issues	BD		✓												✓			✓
		BC				✓		✓	✓										
		MWM																	
10	Personnel incompetency	BD		✓															✓
		BC					✓												
		MWM	✓																
11	Lack of research and development units	BD		✓										✓					
		BC																✓	
		MWM										✓							
12	Lack of industry involvement and collaboration	BD																✓	
		BC				✓	✓												
		MWM								✓	✓								
13	Lack of industrial internet	BD																	✓
		BC					✓												
		MWM																	
14	Lack of international cooperation	BD															✓		
		BC						✓											
		MWM									✓	✓							
15	Lack of learning from advanced nations	BD																	
		BC						✓											
		MWM												✓					

3. Methods

3.1. Method descriptions and procedures

In this study, two techniques were employed: Interpretive Structural Modeling (ISM) and Analytical Hierarchy Process (AHP). Each method has its benefits; they will be explained briefly in the following section, and we describe the study methods and their utilization for result analysis in detail. The research was granted ethical clearance by the Institutional Review Board (IRB) of the School of Business at the University. Informed written consent was obtained from all study participants, who claimed their understanding of the study's purposes and that they would like to participate in the study voluntarily. The respondents were assured that their identities and responses would be kept confidential and maintained in the best interests of academic integrity and in every possible manner. Additionally, they were informed of the study's importance, its potential implications, their role as participants, and that no compensation would be offered. Respondents were assured that they could stop responding and withdraw from the interview at any time. Additionally, the data collection period spanned from January 2025 to April 2025.

3.2. Interpretive Structural Modeling (ISM)

ISM is a logical mathematical approach developed by Sage and Smith [50], which denotes a complex phenomenon among the correlated variables based on the systematic process's structural relationship of interrelated matrices. ISM provides structural modeling based on a group of people's judgments of how elements are interconnected with each other [51]. It helps analyze the factors by developing a structural model [52]. The main benefit of ISM is that it empowers the transformation of unclear and inefficiently expressed systems into well-structured and coherent models [53]. Other characteristics of ISM that support this research are:

- ISM helps break down complex problems into a visual presentation, relying on experts' practical knowledge and experience to divide a complex structure into various sections and create or establish well-defined frameworks [53].
- ISM facilitates the examination of variables in complex structures to reveal their contextual interactions with one another [54].
- Practitioners and researchers are utilizing the ISM method in various research areas to achieve fruitful outcomes from complex and complicated issues [55].

This method needs experts to indicate the variables and analyze intransitive relationships and interactions [56].

3.3. MICMAC analysis

In 1973, the MICMAC technique was introduced by Duperrin and Godet [53]. The MICMAC is a method for examining the cross-impacts of variables in a complex system. ISM results are transferred to the MICMIC process to determine the driving and dependence powers [54] of BDBC-MWM factors in the hospital and healthcare zone. The output of MICMAC analysis is a ranked list of BDBC-MWM factors categorized as autonomous, dependent, linkage, or independent/driving. This information helps prioritize factors for decision-making and strategic planning.

3.4. AHP

AHP is a quantitative multiple decision-making approach designed by Saaty [57]. Some limitations exist in the application of AHP, such as subjective choice selection, a crisp environment, the risk of uncertainty, and an unstable decision scale. To solve these issues, a fuzzy method was combined with AHP. The fuzzy AHP method integrates vagueness and uncertainty by integrating the findings of decision-makers using linguistic variables.

4. **Step-by-step scheme**

A multi-level methodological approach combining ISM, MICMAC, and AHP is a comprehensive research method used to analyze and model complex associations among variables (as shown in Figure 2).

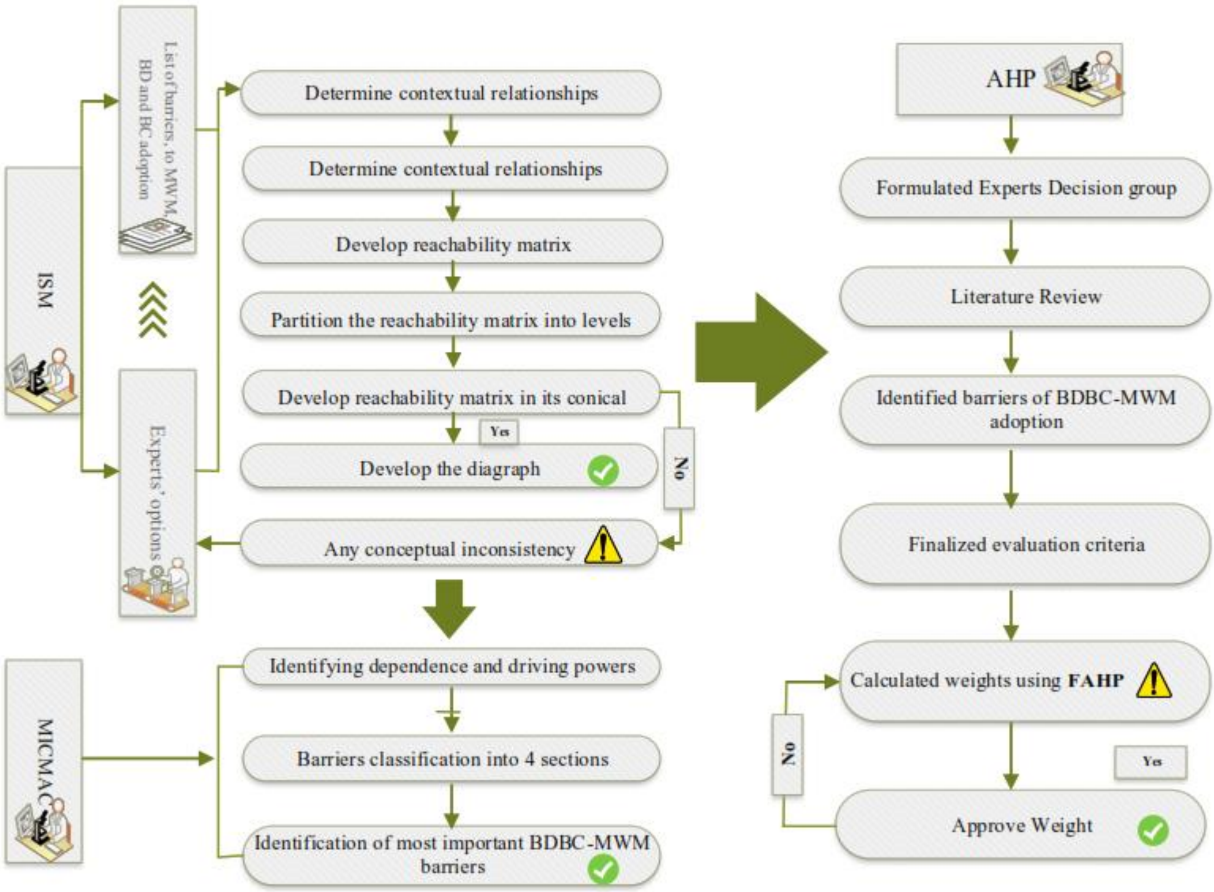

Figure 2. Step-by-step scheme of study.

Here are the steps involved in this integrated methodology:

4.1. ISM phase

Develop an SSIM by examining different types of associations between variables.
Create an initial reachability matrix to determine the reachability of one variable by another, represented in binary values (0 or 1).
Construct the final reachability matrix by removing transitivity among variables.
Derive different iterations and levels of variables with the help of the final reachability matrix.
Generate the Digraph (directed graph) of the variables to visualize the hierarchy and interconnections.

4.2. MICMAC phase

Conduct a MICMAC analysis to classify the variables into different groups based on their driving power and dependence.
Variables are typically categorized into four groups: Autonomous, Dependent, Linking, and Driving.
Identification of the most critical factors.

4.3. AHP phase

4.3.1. Phase 1. Evaluation of barriers to the adoption of BDBC-MWM

In the early stage of mythology, a consortium of experts, including scholars, industry professionals, and consultants, was established. Subsequently, barriers associated with BDBC-MWM were assessed and examined based on the literature and expert opinions.

4.3.2. Phase II. Involves the implementation of the Fuzzy Analytical Hierarchy Process (FAHP)

If Ă1 = (*p1, q1, r1*) and Ă2 = (*p2, q2, r2*) are characterized by 2 triangular fuzzy numbers, then the following algebraic operation is executed.

$$\breve{A}_1 \oplus \breve{A}_2 = (p_1, q_1, r_1) \oplus (p_2, q_2, r_2) = (p_1 + p_2, q_1 + q_2, r_1 + r_2) \quad (1.1)$$

$$\breve{A}_1 -- \breve{A}_2 = (p_1, q_1, r_1) - (p_2, q_2, r_2) = (p_1 - r_2, q_1 - q_2, r_1 - p_2) \quad (1.2)$$

$$\breve{A}_1 \otimes \breve{A}_2 = (p_1, q_1, r_1) \otimes (p_2, q_2, r_2) = (p_1 p_2, q_1 q_2, r_1 r_2) \quad (1.3)$$

$$\breve{A}_1 \emptyset \breve{A}_2 = (p_1, q_1, r_1) \emptyset (p_2, q_2, r_2) = (p_1/r_2, q_1/q_2, r_1/p_2) \quad (1.4)$$

$$\alpha \otimes \breve{A}_2 = (\alpha p_1, \alpha q_1, \alpha r_1) \text{ where } \alpha > 0 \quad (1.5)$$

$$\breve{A}_1^{-1} = (p_1, q_1, r_1)^{-1} = \left(\frac{1}{r_1}, \frac{1}{q_1}, \frac{1}{p_1}\right) \quad (1.6)$$

To instrument the FAHP constructed on Chang's extent analysis approach

$$M_{g_i}^1, M_{g_i}^2, M_{g_i}^3, \dots, M_{g_i}^m \quad (1.7)$$

The goal set ($= 1,2,3,4,5, \dots, n$), symbolized as g_i and all the $M_{g_i}^j$ $(j = 1,2,3,4,5, \dots, m)$ are triangular fuzzy number is shown in Table 4. The Chang's approach steps are resulting:
Step 1: (H_i) the fuzzy synthetic extent value with to ith criterion is demarcated as:

$$H_i = \sum_{j=1}^{m} M_{g_i}^{j} \times \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} \tag{1.8}$$

$$\sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{j=1}^{m} p_{ij}, \sum_{j=1}^{m} q_{ij}, \sum_{j=1}^{m} r_{ij}\right) \tag{1.9}$$

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} = \left(\frac{1}{\sum_{n}^{i=1}\sum_{m}^{j=1} r_{ij}}, \frac{1}{\sum_{n}^{i=1}\sum_{m}^{j=1} q_{ij}}, \frac{1}{\sum_{n}^{i=1}\sum_{m}^{j=1} p_{ij}}\right) \tag{1.10}$$

where r is the sign for the lowest value, q is used for the mid values, and p is the signified as the most significant value.

Step 2: The degree of possibility of D_2, signified as (p_2, q_2, r_2) being greater than or equal to D_1, signified as (p_1, q_1, r_1), is defined as:

$$V(D_2 \geq D_1) = \sup_{y \geq x}[\min(\mu_{d1}(x), \mu_{d2}(y))]$$

The equation below shows the axis membership function for every single criteria with respect to two values, x and y.

$$V(D_2 \geq D_1) = \begin{cases} 1 & if\ q_2 \geq q_1 \\ 0 & if\ p_1 \geq r_2 \\ \frac{p_1 - r_2}{(q_2 - r_2) - (q_1 - p_1)} & otherwise \end{cases} \tag{1.11}$$

where μd is a maximal intersection point between $\mu d_1$and μd_1 (Figure 3).

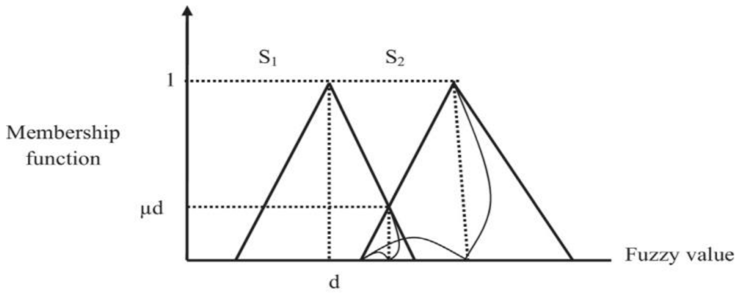

Figure 3. The intersection of fuzzy numbers.

In order to combine $D_1$and D_2, we needed both $V(D_1 \geq D_2)$ and $V(D_2 \geq D_1)$.
Step 3. The degree of probability of a convex fuzzy number $D \geq$ K convex fuzzy numbers $D_i(i = 1,2, \dots, k)$ can be described by
$V(D \geq D_1, D_2, \dots, D_k) = V\ [(D \geq D_1), (D \geq D_1), \dots, (D \geq D_k)]$

$$= \min V(D \geq D_i), \quad i = 1,2, \dots, k \tag{1.12}$$

Let's assume $d'(B_i) = \min V(D_i \geq D_k)$ then weight vectors for $k = 1,2, \dots, n, k \neq i$ are denoted by the equation (1.13) as:

$$W' = (d'(B_1), d'(B_2), \dots, d'(B_m))^T \tag{1.13}$$

Table 2. Description of barriers title.

Sr#	Barriers	Description
1	Lack of training and workshops	The high cost of IT BD (Big Data) and BC (Blockchain) training and skills development programs for IT professionals is a barrier to medical waste Management practices (MWM)
2	Inadequate technological infrastructure	Most of the present technologies BD (Big Data) and BC (Blockchain) are still unable to meet current infrastructure requirements in MWM (Medical Waste Management) practice.
3	Insufficient resources	We do not have enough funds to invest in many metropolitan city innovation projects and MWM (Medical Waste Management) practices, we need to find a way to support them differently
4	Lack of skilled IT personnel	Insufficient cost of IT, lack of professionals and consultancies, installation, operation, maintenance, and training are essential barriers to MWM (Medical Waste Management) practices in Metropolitan cities
5	Insufficient information	Insufficient information about the implications of BD (Big Data) and BC (Blockchain) is the main obstacle in the medical waste management practice (MWM)
6	Insufficient knowledge and awareness regarding BDBC-MWM	Lack of expertise and knowledge may increase data input errors, data loss, or confound data analysis and interpretation which is a solid hurdle in the development of metropolitan cities and MWM practices
7	Lack of rules, regulations, and policies	Lack of appropriate laws, regulations, or directives for the Medical Waste Management (MWM) practices and metropolitan cities development
8	Lack of Management Support	The lack of vision on how IT management can be effectively imposed on Medical Waste Management practices (Medical Waste Management) and development of the metropolitan cities
9	Data security issues	Data security and privacy are some of the significant barriers to MWM (Medical Waste Management) practices in the development of metropolitan Cities
10	Personnel incompetency	Lack of staff capability is a major issue for BDBC-MWM practice in Metropolitan cities
11	Lack of research and development units	Lack of research and development units are main cause of not implementing BDBC-MWM
12	Lack of industry involvement and collaboration	Lack of industry involvement in BDBC-MWM in metropolitan cities is the main barrier to it.
13	Lack of industrial internet	Due to poor internet connectivity, there may be issues in BD (Big Data) and BC (Blockchain) implementation in medical waste management practices (MWM) of metropolitan cities
14	Lack of international cooperation	The implementation of collaborative approaches to manage the massive volume and flow of medical waste on a global scale is difficult due to the lack of mutual understanding and profit-sharing
15	Lack of learning from advanced nations	Insufficient learning from advanced nation's techniques regarding BDBC-MWM

4.4 Application of research methodology

We debated the process of ISM in detail. In the ISM process, all stages' outcomes were fully defined and demonstrated by their relevant results.

4.4.1. Identification of BDBC-MWM barriers

The ISM process identifies and determines the significant variables of the complex problem within the complex system. As we argued above, we selected and extracted persuasive barriers based on expert opinions and a literature review of past studies.

According to other studies, there are 11 barriers, which correspond to a precise and integrated combination of significant factors. According to the experts' opinion method, a group of experts excluded some BDBC-MWM elements, which were deemed less valid and slightly similar in the MWM context. Besides, the expert panel proposed four pioneering elements due to their significance in MWM practices. Finally, our experts finalized 15 key barriers of BDBC-MWM as essential factors for performing MWM practices effectively. In Table 2, the selected barriers of BDBC-MWM are defined and explained.

5. Results and discussion

5.1. Results of ISM

5.1.1. Establishing variable contextual relationships

A key component of the ISM process is the experts' practical, experienced knowledge and ability to establish a contextual relationship between relevant variables and their judgments.

Therefore, seven experts were selected from the Delphi panel to examine the interrelationship between variables. The experts finalized the barriers list for the BDBC-WMW by examining the relationship between each variable in an empty SSIM (structural self-interaction matrix) sheet. The findings were discussed with the experts, and contextual relationships were developed with their judgments and practical knowledge. Table 3 and Figure 4 present the pairwise assessment of BDBC-MWM in terms of SSIM.

For the SSIM development, a panel of experts scrutinized the interrelationships among barriers. These barriers' relationships denoted and defined symbols such as V, A, X, and O in row (i) and column (j).

V: This symbol denotes that the barrier (i) will assist in convincing the barrier (j);

A: This symbol denotes that barrier (j) will be attained or surpassed by a barrier (i);

X: This symbol denotes that the barriers (i) and (j) will help persuade each other

O: This symbol denotes that the barriers (i) and (j) are contradictory.

Table 3. Structural Self-Interaction Matrix.

Sr.	Barrier Name	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15
1	Lack of training and workshops		X	A	V	V	V	A	A	O	V	A	A	O	O	V
2	Inadequate technological infrastructure			A	V	A	V	A	A	V	V	O	A	X	V	A
3	Insufficient resources				V	V	V	O	V	O	V	V	V	V	V	V
4	Lack of skilled IT personnel					V	V	O	A	V	O	V	A	X	O	O
5	Insufficient information						V	O	A	V	V	A	A	A	V	V
6	Insufficient knowledge and awareness regarding BDBC-MWM							O	A	O	V	A	A	A	A	O
7	Lack of rules, regulations and policies								V	O	V	V	V	O	O	O
8	Lack of Management support									O	V	V	V	O	V	V
9	Data security issues										A	O	A	A	A	O
10	Personnel incompetency											V	A	O	O	A
11	Lack of research and development units												A	V	O	X
12	Lack of industry involvement and collaboration													O	V	V
13	Lack of industrial internet														O	O
14	Lack of international cooperation															O
15	Lack of learning from advanced nations															

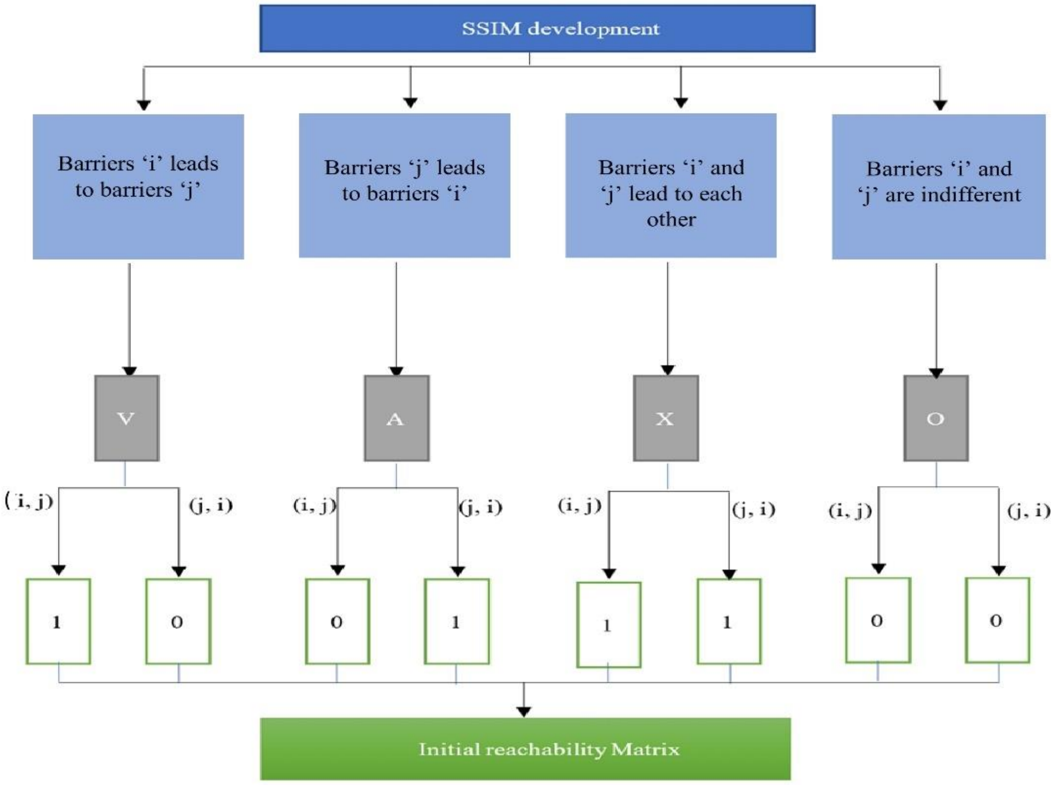

Figure 4. Transformation rules from SSIM to IRM.

5.1.2. Establishing the Initial Reachability Matrix (IRM)

We then developed initial and final reachability matrices based on the SSIM results. initial reachability matrix (IRM) was developed by SSIM, adapting symbols (V, A, X, and O). It was designed using binary coding, where 1 and 0 represent the direction of their nature, as shown in the transformation rules (Figure 5). These can be explained as follows:

When V is the sign of entry (i and j), this sign indicates that entry (i and j) =1 and entry (j and i) =0.
When A is the sign of entry (i and j), this sign indicates that entry (i and j) =0 and entry (j and i) =1.
When X is the sign of entry (i and j), this sign indicates that entry (i and j) =1 and (j and i) =1.
When O is the sign of entry (i and j), this sign indicates that entry (i and j) =0 and (j and i) =0.
Results for IRM are shown in Table 4.

5.1.3. Establishing final reachability matrix

Table 4. IRM.

Sr.	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15
1	1	1	0	1	1	1	0	0	0	1	0	0	0	0	1
2	1	1	0	1	0	1	0	0	1	1	0	0	1	1	0
3	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1
4	0	0	0	1	1	1	0	0	1	0	1	0	1	0	0
5	0	1	0	0	1	1	0	0	1	1	0	0	0	1	1
6	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0
7	1	1	0	0	0	0	1	1	0	1	1	1	0	0	0
8	1	1	0	1	1	1	0	1	0	1	1	1	0	1	1
9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0
11	1	0	0	0	1	1	0	0	0	0	1	0	1	0	1
12	1	1	0	1	1	1	0	0	1	1	1	1	0	1	1
13	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0
14	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0
15	0	1	0	0	0	0	0	0	0	1	1	0	0	0	1

To configure the final reachability matrix (FRM), we required specifying transitive relationships, where the developed relationship among two variables: 1st and 2nd, between "2nd and 3rd" variables could denote the relationship among 1st and 3rd variables. If variable X is linked to variable Y (X→Y) and variable Y is also linked to variable Z (Y→Z), then the X and Z relationship is transitive. This mathematical equation can better determine the development of two matrices, IRM to FRM, in light of the transitivity process.

$$\text{If} \quad (T\ ik = 1) \wedge (T\ ik = 1) \wedge (T\ ij = 0), \text{ then } (T\ ij = 1^*) \tag{2}$$

The symbol ‘T’ is denoted as IRM, in which k ≠ i & k ≠ j and i, j denotes rows and columns individually, and in the transitivity process, k indicates the reference cell (i, j). The final reachability matrix is depicted in Table 5.

Table 5. FRM.

Sr. No.	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	Driv. power
1	1	1	0	1	1	1	0	0	1*	1	1*	0	1*	1*	1	**11**
2	1	1	0	1	1*	1	0	0	1	1	1*	0	1	1	1*	**11**
3	1	1	1	1	1	1	0	1	1*	1	1	1	1	1	1	**14**
4	1*	1*	0	1	1	1	0	0	1	1*	1	0	1	0	1*	**10**
5	1*	1	0	1*	1	1	0	0	1	1	1*	0	1*	1	1	**11**
6	0	0	0	0	0	1	0	0	1*	1	1*	1*	0	0	0	**5**
7	1	1	0	1*	1*	1*	1	1	1*	1	1	1	1*	1*	1*	**14**
8	1	1	0	1	1	1	0	1	1*	1	1	1	1*	1	1	**13**
9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	**1**
10	1*	0	0	0	1*	1*	0	0	1	1	1	0	1*	0	0	**7**
11	1	1*	0	1*	1	1	0	0	1*	1*	1	0	1	1*	1	**11**
12	1	1	0	1	1	1	0	0	1	1	1	1	1*	1	1	**12**
13	1*	1	0	1	1	1	0	0	1	1*	1	0	1	1*	1*	**11**
14	0	0	0	0	0	1	0	0	1	1*	1*	1*	0	1	0	**6**
15	1*	1	0	1*	1*	1*	0	0	1*	1	1	0	1*	1*	1	**11**
Dep. Power	**12**	**11**	**1**	**11**	**12**	**14**	**1**	**3**	**15**	**14**	**14**	**6**	**12**	**11**	**11**	**148**

5.1.4. Partitioning level

When finalizing FRM, we described the variable hierarchy based on the level partition context. In the FRM matrix, every identical barrier is evaluated based on reachability and antecedent sets [58]. A set of reachability is formed by itself and other barriers, which it assists in overcoming. The antecedent set is also comprised of its barriers, which either drive or support its realization. After forming antecedent and reachability sets for each barrier, we identified their intersections within these sets. At level I, those elements are comprised, where the intersections and reachability sets are the same. The first level contains the barrier (9), and the data security issue, revealing the top dependency levels (6). This method is iterated to reach the next level, but the formerly recognized common variables are eradicated at every level. The remaining reachability and intersection set at level II are iterated, as outlined in Table 6, with insufficient knowledge and awareness regarding BDBC-MWM.

At level III, the barrier is personnel incompetence. Barriers cited at the IV iteration level include a lack of skilled IT personnel, insufficient research and development units, and inadequate international cooperation. At the iteration level V, barriers include a lack of training and workshops, inadequate technological infrastructure, insufficient information, a lack of industrial internet, and a failure to learn from advanced nations. Lack of industry involvement and collaboration, as well as a lack of management support, are the barriers at iteration levels VI and VII, respectively. The last iteration level (VIII) contains two barriers: Insufficient resources and a lack of rules, regulations, and policies.

Table 6. Levels of iteration.

Sr#	Reachability Set	Antecedent set	Intersection	Level
1	1,2,4,5,6,9,10,11,13,14,15	1,2,3,4,5,7,8,10,11,12,13,15	1,2,4,5,10,11,13,15	V
2	1,2,4,5,6,9,10,11,13,14,15	1,2,3,4,5,7,8,11,12,13,15	1,2,4,5,11,13	V
3	1,2,3,4,5,6,8,9,10,11,12,13, 14,15	3	3	VIII
4	1,2,4,5,6,9,10,11,13,15	1,2,3,4,5,7,8,11,12,13,15	1,2,4,5,11,13	IV
5	1,2,4,5,6,9,10,11,13,14,15	1,2,3,4,5,7,8,10,11,12,13,15	1,2,4,5,10,11,13,15	V
6	6,9,10,11,12	1,2,3,4,5,6,7,8,10,11,12,13,14,15	6,10,11,12	II
7	1,2,4,5,6,7,8,9,10,11,12,13,14,15	7	7	VIII
8	1,2,4,5,6,8,9,10,11,12,13,14,15	3,7,8	8	VII
9	9	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	9	I
10	1,5,6,9,10,11,13	1,2,3,4,5,6,7,8,10,11,12,13,14, 15	1,5,6,10,11,13	III
11	1,2,4,5,6,9,10,11,13,14,15	1,2,3,4,5,6,7,8,10,11,12,13,14, 15	1,2,4,5,6,10,11,13,14,15	IV
12	1,2,4,5,6,9,10,11,12,13,14,15	3,6,7,8,12,14	6,12,14	VI
13	1,2,4,5,6,9,10,11,13,14,15	1,2,3,4,5,7,8,10,11,12,13,15	1,2,4,5,10,11,13,15	V
14	6,9,10,11,12,14	1,2,3,5,7,8,11,12,13,14,15	11,12,14	IV
15	1,2,4,5,6,9,10,11,13,14,15	1,2,3,4,5,7,8,11,12,13,15	1,2,4,5,11,13,15	V

5.1.5. Establishing the structure of ISM

The final step in the ISM method was to develop the structural model and graph. The final ISM model illustrates the interrelationships between the BDBC-WMM and its factors in the FRM, which was established at the partitioning level of the reachability matrix. The digraph of ISM has eight levels; at the top level, there is only one barrier: Data security issues. The barriers have the lowest driving power and the highest dependency power at this level. Therefore, these are significantly dependent on the below-level barriers. The next step of the model shows insufficient knowledge and awareness regarding BDBC-MWM. At this level, barrier dependence power is higher than the first level, but dependence power is the same as high as the first level.

The next layer in the model represents personnel incompetence. This barrier has a significant impact on lower-level barriers and a substantial influence on upper-level barriers. The subsequent level reveals a shortage of skilled IT personnel, inadequate research and development units, and a lack of international cooperation. At this level, barriers have a strong influential interaction with other linked barriers and a strong driving power in our digraph. Another layer of digraph reveals a lack of training and workshops, inadequate technological infrastructure, insufficient information, a lack of industrial internet, and a lack of learning from advanced nations. At this level, these barriers have a substantial impact on lower-level barriers and a solid, influential link to the level above. The next level of our model depicts a lack of industry involvement and collaboration. This level is equivalent to the one below, as it also has a significant impact on lower-level barriers and a strong, influential link to the level above.

The second level of our model displays a lack of management support. At this stage, this barrier significantly influences the barriers above it and impacts those at the lower level. The last layer of our digraph represents key barriers: Insufficient resources and a lack of rules, regulations, and policies.

Last-level barriers have a strong influential linkage over other interrelated factors and the strongest driving power in our model (shown in Figure 5).

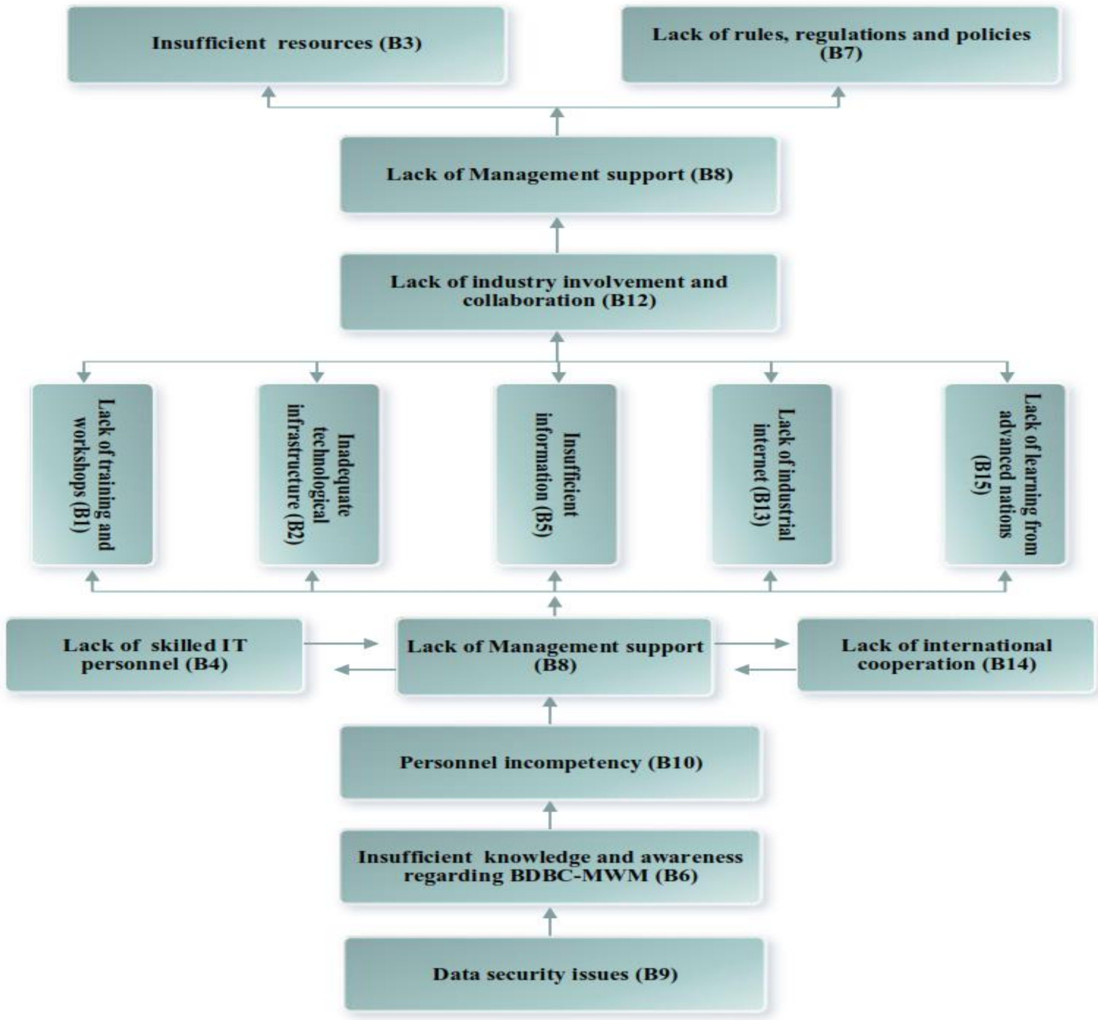

Figure 5. Interpretive Structure Model of Barriers

In 1973, Duperrin and Godet developed a technique named MICMAC, which investigates and analyzes the structure of complex systems. The MICMAC method determines the complex system variables based on their driving and dependence power [30]. The MICMAC method calculates variable dependence and driving power by totaling vertical and horizontal axes. In the binary coding system of MICMAC, the sum of each row represents the variable's driving power, whereas the sum of each column identifies its dependence power. In this study, to elaborate on the accuracy and sensitivity of the outcomes, we employed the MICMAC technique to anticipate the presence and quantify the strength of relationships among the variables.

According to Saxena and Vrat [59], in a complex system, its key factors can be better accomplished by recognizing the variables, direct and indirect influences, and describing the existence under study. In the sight of the estimated MICMAC, the Binary Matrix of Direct Influence (BMDI) was developed by transforming the diagonal entries of IRM to zero. In the BMDI, each cell shows the range of a variable that directly impacts the other variables. Typically, in fuzzy MICMAC analysis, fuzzy triangular linguistic terms are employed to address the ambiguity caused by the practical uncertainty and subjectivity inherent in human knowledge and judgments. Thus, based on our expert opinions, we used the fuzzy function to compute contextual relationship strength among digraph variables.

The triangular relationship can be defined in a mathematical function, in which *r* indicates the upper limit of the relationship, *l* indicates the lower limit, and m indicates the value. It can be described as *l* > *m* > *r*. The function of a triangular relationship is defined in equation (3).

$$\mu\tilde{A}(x) = \begin{cases} \dfrac{x - l}{m - l} & l \geq x \leq m \\ \dfrac{r - x}{r - m} & m \geq x \geq r \\ 0 & \end{cases} \tag{3}$$

The MICMAC technique can be applied to the expert's judgments about the interrelationship of linguistic variables in terms of the nature of qualitative consideration, which is represented by fuzzy triangular numbers. After that, we investigated the relationship between applied linguistic terms and BDBC-MWM with the help of some experts to determine the influence of BDBC-MWM on each other. To obtain a linguistic assessment direct relationship matrix, we applied the values to the BMDI.

Qureshi, Kumar [60] stated that the matrix is increased frequently up to the level of driving and dependence power steadied. This type of multiple ambiguity is used to examine and study the nature of indirect dependence and driving power. It can be traced to the influence of transformation by other transitional variables [53]. It enables us to identify the BDBC-MWM that may not possess strong driving or dependence power, but are essential components for the method in the overall phenomenon [61]. Using the principle of fuzzy matrix multiplication, we used the multiplication method defined in the equation 4.

C = A. B = max n [min (ain, bnj)] (4)

The MICMAC stabilized the matrix for BDBC-MWM in the hospital and healthcare sector, as shown Figure 5, in the same was as in the MICMAC, 0 and 1 coding system, and we sum up values in each row and compute the driving powers of the MICMAC model.

The MICMAC framework in Figure 6 describes the dependence and driving powers of BDBC-MWM barriers and divides them into four sections, as follows:

Section 1 ***Autonomous****:* Variables in this section have low driving and dependence powers, and these are quietly separated from other variables in the ISM model. Therefore, these variables have a low influence on the system.

Section 2 ***Linkage:*** Variables in this section have strong driving and dependence powers, causing instability in the model, as any activity on one variable affects the others.

Section 3 ***Dependent Variables:*** Variables in this section have strong dependence powers and weak driving powers, and they are affected by other factors. They do not have any influence on other factors.

Section 4 ***Independent***: Variables in this section have low dependence powers but strong driving powers. They are habitually considered significant variables.

In the MICMAC method analysis, as demonstrated in Figure 6, most BDBC-MWM barriers are situated in dependent and independent sections. It means that several variables strongly influence other dominant factors and can affect MWM implementations. The essential BDBC-MWMs driving factors, like 3, 7, 8, and 12, are cited in the independent cluster. These elements have a significant impact on other metropolitan MWM barriers; therefore, they should be carefully addressed. BDBC-MWM barriers in the independent section are important factors in MWM implementation practices.

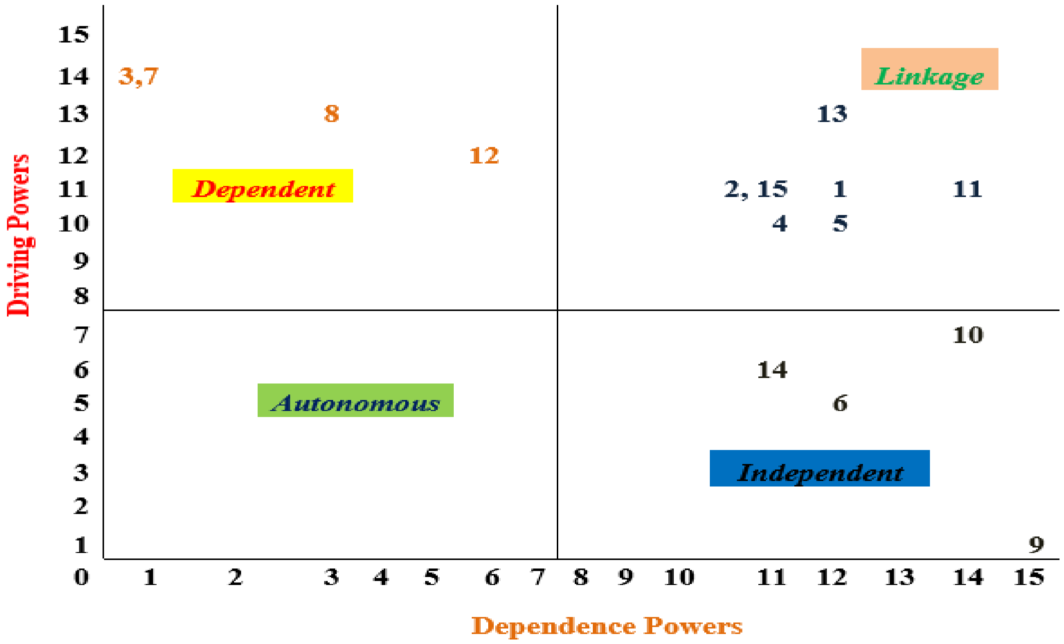

Figure 6. The MICMAC framework.

In the section on the dependent, several barriers were identified. Five barriers are in this cluster: 6, 9, 10, and 14. In our MICMAC model, none of the factors were placed in the autonomous cluster. The absence of BDBC-MWM barriers in the autonomous cluster shows that all the deliberated barriers have favorable relationships. Seven barriers were placed in the linkage cluster, emphasizing their insecure nature due to high dependence and driving powers. Any variation in autonomous quadrant factors would have a corresponding impact on other factors and responses to themselves. These extremely interlinked barriers are 1, 2, 4, 5, 11, 13, and 15.

5.3. Results of AHP

5.3.1. Application of the proposed method for BDBC-MWM adoption in medical and healthcare projects

5.3.1.1. Phase 1: Identification of SETs barriers to adoption of BDBC-MWM

The panel of experts was established, comprising 10 personnel, which included 3 doctors, 2 nurses, 2 academicians, 1 consultant, 1 dentist, and 1 pharmacist (see Table 7). Fifteen barriers (sub-criteria) were extracted from relevant and existing literature, as well as experts' discussions (Table 8).

Table 7. Respondents demographics profile.

No	Code	Type of Profession	Gender	Age	Education	Post	Experience	Company Size
1	D1	Doctor	Male	55	Master	Director	30	30
2	D2	Doctor	Male	45	Master	Director	20	105
3	D3	Doctor	Female	30	Bachelor	Director	10	150
4	NS1	Nurse	Female	35	Bachelor	Associate Managing Director	13	13
5	NS2	Nurse	Female	25	Bachelor	Associate Managing Director	5	55
6	AC1	Academician	Male	55	PhD	Professor	8	2400
7	AC2	Academician	Male	40	PhD	Associate Professor	5	2400
8	CT1	Consultant	Male	50	Bachelor	Director	-	-
9	DT1	Dentist	Male	52	Bachelor	CEO MD Waste Management	12	2500
10	Ph1	Pharmacist	Male	42	Bachelor	Assistant Director	9	30

Table 8. Barriers of BDBC-MWM extracted from past studies.

Criteria	Code	Sub-criteria	[10]	[30]	[31]	[33]	[35]	[36]	[44]	[39]	[62]	[7]	[47]	[37]	[32]	[38]	[49]
Government Barriers	GB1	Lack of research and development units	✓		✓	✓				✓		✓		✓			✓
	GB2	Lack of international cooperation		✓					✓					✓			
	GB3	Lack of rules, regulations, and policies		✓			✓	✓		✓			✓	✓	✓	✓	
	GB4	Lack of industry involvement and collaboration		✓	✓						✓		✓		✓		
	GB5	Lack of learning from advanced nations						✓					✓				✓
Human Barriers	HB1	Lack of training and education of staff					✓				✓						
	HB2	Lack of skilled IT personnel	✓			✓		✓					✓			✓	✓
	HB3	Incapable staff capability		✓			✓		✓			✓		✓		✓	✓
Economic and Organizational Barriers	EOB1	Lack of Management support			✓			✓			✓			✓	✓		
	EOB2	Lack of industrial internet						✓					✓				✓
	EOB3	Insufficient resources		✓	✓				✓			✓	✓		✓	✓	✓
	EOB4	Lack of knowledge about BDBC-MWM		✓	✓			✓				✓					✓
Technological Barriers	TB1	Inadequate technological infrastructure	✓			✓			✓		✓			✓			
	TB2	Lack of information		✓			✓		✓			✓					✓
	TB3	Data security issue	✓			✓			✓				✓			✓	

5.3.1.2. Phase 2: FAHP was used to compute the barrier weights for the adoption of BDBC-MWM

For this study, four criteria and 15 sub-criteria were developed through pairwise comparisons of every element. The TFN numbers were adopted to finalize the process, which is depicted in Table 9. The process for allocating weights to criteria and sub-criteria through fuzzy comparison matrices is demonstrated in Tables 9−16. All calculations for key values were performed using MS Excel.

Table 9. TFN of linguistic comparison matrix.

Linguistic variables	Assigned TFN
Equal	(1,1,1)
Very low	(1,2,3)
Low	(2,3,4)
Medium	(3,4,5)
High	(4,5,6)
Very High	(5,6,7)
Excellent	(6,7,8)

Table 10. The fuzzy comparison of matrix of the criteria.

	GB			HB			EOB			TB			Weight	Rank
GB	1	1	1	1	2	3	0.33	0.5	1	2	3	4	0.297	1
HB	0.33	0.5	0.1	1	1	1	2	3	4	0.33	0.5	1	0.247	3
EOB	1	2	3	0.25	0.33	0.5	1	1	1	1	2	3	0.259	2
TB	0.25	0.33	0.5	1	2	3	0.33	0.5	1	1	1	1	0.195	4

Table 11. The pairwise comparison of GB sub criteria w.r.t criteria.

	GB1			GB2			GB3			GB4			GB5			Weight	Rank
B1	1	1	1	0.25	0.33	0.5	1	2	3	2	3	4	4	5	6	0.319	1
GB2	2	3	4	1	1	1	1	2	3	0.33	0.5	1	1	2	3	0.253	3
GB3	0.33	0.5	1	0.33	0.5	1	1	1	1	2	3	4	3	4	5	0.263	2
GB4	0.25	0.33	0.5	1	2	3	0.25	0.33	0.5	1	1	1	0.25	0.33	0.5	0.057	5
GB5	0.16	0.2	0.25	0.33	0.5	1	0.2	0.25	0.33	2	3	4	1	1	1	0.105	4

Table 12. The pairwise comparison of EOB sub criteria w.r.t criteria.

	EOB1			EOB2			EOB3			EOB4			Weight	Rank
EOB1	1	1	1	4	5	6	1	2	3	0.33	0.5	1	0.312	1
EOB2	0.16	0.2	0.25	1	1	1	4	5	6	0.25	0.33	0.5	0.225	4
EOB3	0.33	0.5	1	0.16	0.2	0.25	1	1	1	4	5	6	0.238	2
EOB4	1	2	3	2	3	4	0.16	0.2	0.25	1	1	1	0.233	3

Table 13. The pairwise comparison of HB sub criteria w.r.t criteria.

	HB1			HB2			HB3			Weight	Rank
HB1	1	1	1	0.25	0.33	0.5	2	3	4	0.377	1
HB2	1	2	3	1	1	1	0.33	0.5	1	0.291	2
HB3	0.25	0.33	0.5	1	2	3	1	1	1	0.230	3

Table 14. The pairwise comparison of TB sub criteria w.r.t criteria.

	TB1			TB2			TB3			Weight	Rank
TB1	1	1	1	0.25	0.33	0.5	2	3	4	0.377	1
TB2	1	2	3	1	1	1	0.33	0.5	1	0.291	2
TB3	0.25	0.33	0.5	1	2	3	1	1	1	0.230	3

The computation of the fuzzy synthetic extent for the 4 criteria was performed using Equation (1.10), and the subsequent final values for the criteria and sub-criteria are presented in Table 12.

S (GB) = $(4.33,\ 6.5,\ 9) \otimes (13.83,\ 20.66,\ 29)$-1
= (0.313, 0.314, 0.310)
S (HB) = $(3.66,\ 5,\ 7) \otimes (13.83,\ 20.66,\ 29)$-1
= (0.216, 0.242, 0.241)
S (EOB) = $(3.25,\ 5.33,\ 7.5) \otimes (13.83,\ 20.66,\ 29)$-1
= (0.234, 0.257, 0.258)
S (OB) = $(2.58,\ 3.8,\ 5.5) \otimes (13.83,\ 20.66,\ 29)$-1
= (0.186, 0.182, 0.189)

The values of V are calculated using equation (1.11), as shown in Table 15.

Table 15. V values for criteria.

	GB	HB	EOB	OB
GB		1	1	1
HB	0.830		1	1
EOB	0.874	0.960		1
OB	0.657	0.827	0.797	

Then, the minimum degree of possibility was computed through equation (1.12), which is stated as:

$$m(OB) = \min\ V(S_1\ =\ S_4) = \min(0.657, 0.827, 0.797, 0.830) = 0.657$$

By retaining this way, we could compute the minimum degree of probability for the remaining condition.

Later, the weight vector is presented as

W_v= (1, 0.830, 0.874, 0.657) T

Finally, the last weights of the criteria can be achieved through the process of normalizing the weights vector.

$$\mathrm{W} = (\ 0.297, 0.247, 0.259, 0.195)$$

Due to the same process and space limits, the remaining calculated weight values are not shown.

Table 16. Final ranking of BDBC-MWM barriers.

Criteria	Weight	Sub-criteria	Weight	Final weight	Global rank
Government barriers	0.297	GB1	0.319	0.094743	1
		GB2	0.253	0.075141	5
		GB3	0.263	0.078111	4
		GB4	0.057	0.014763	15
		GB5	0.105	0.031185	14
Human barriers	0.247	HB1	0.377	0.093119	2
		HB2	0.291	0.071877	7
		HB3	0.230	0.056810	11
Economic and Organizational barriers	0.259	EOB1	0.312	0.080808	3
		EOB2	0.225	0.058275	10
		EOB3	0.238	0.061642	8
		EOB4	0.233	0.060347	9
Technological barriers	0.195	TB1	0.377	0.073515	6
		TB2	0.291	0.056745	12
		TB3	0.230	0.044850	13

5.4. Results and discussion from the AHP analysis

In this study, AHP was adopted to evaluate the barriers to the use of BDBC-MWM in MWM. Results, as shown in Table 16, indicate that the Government Barriers, with a weight value of 0.297, also have the most considerable impact, highlighting that policy issues are the primary concern. In terms of government-related problems, GB1 (lack of research and development units**)** is the highest barrier with global rank 1st, having a weight value equal to 0.0947, followed by GB2 **(**lack of rules, regulations, and policies**)**, G3 **(**lack of international cooperation), and G4 (lack of learning from advance nations) ranked 4th and 5th, respectively. These results underscore the importance of strict policy guidelines, a regulatory framework, and government R&D investment to encourage the diffusion of BD and BC technologies, as revealed in Table 16 and Figure 7.

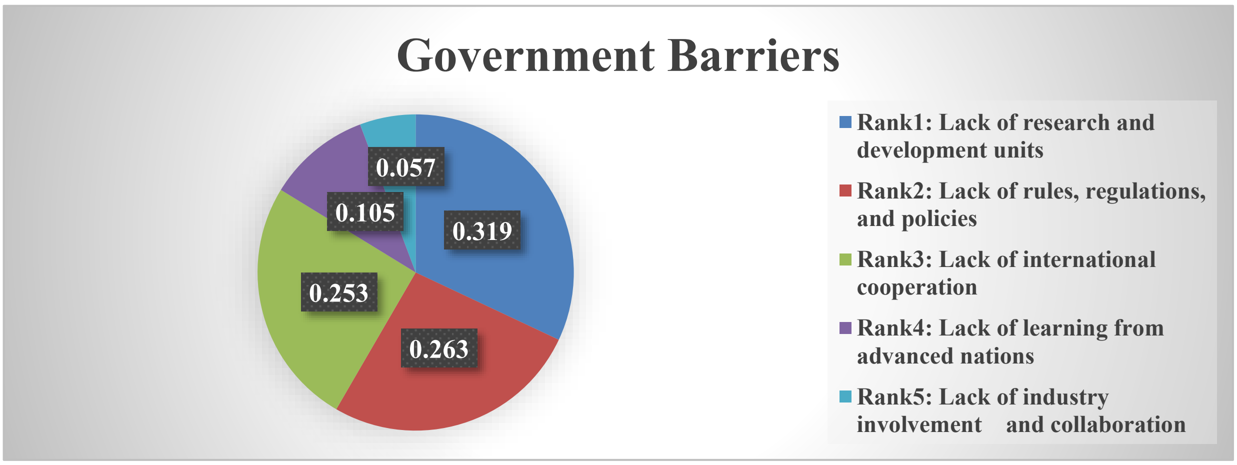

Figure 7. Government Barriers.

The second most significant barriers are Human Barriers with a weight of (0.247). Notably, the lack of training and education of staff (HB1), which has a weight of 0.0931, is identified as an essential barrier with a global rank of 2nd. Lack of skilled IT personnel (HB2) ranked 7th, and Inadequate staff capability (HB3) ranked 11th (as shown in Table 16 and Figure 8). In the context of healthcare personnel capability, these challenges pose additional requirements for specialized training programs to equip healthcare staff for BD and BC usable activities. Addressing these human resource challenges is crucial for the effective implementation of these technologies in medical waste disposal.

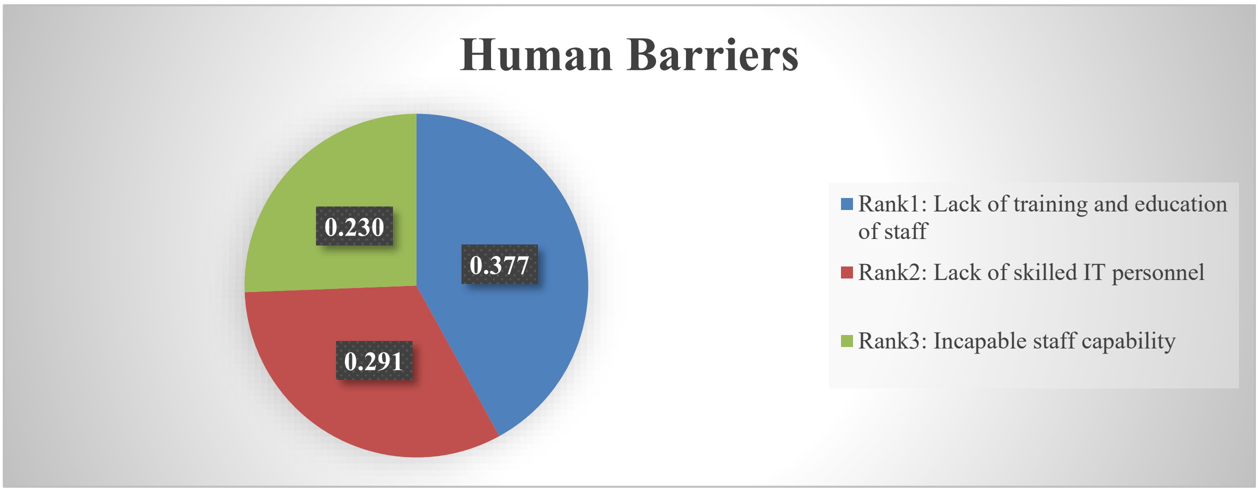

Figure 8. Human Barriers.

Economic and Organizational Barriers outcomes reveal a lack of management support (EOB1) on the 3rd ranked with a weight of 0.0808, so there is insufficient resources (EOB3) and lack of knowledge about BDBC-MWM (EOB4) (shown in Table 16 and Figure 9). These results support the fact that more management dedication is needed to implement data-driven and BC-based MWMMWM. Moreover, another limitation that needs to be addressed is the insufficient resources (ranked 8th) and lack of knowledge about BDBC-MWM (ranked 9th), which should be addressed with the help of strategic investment and capacity building.

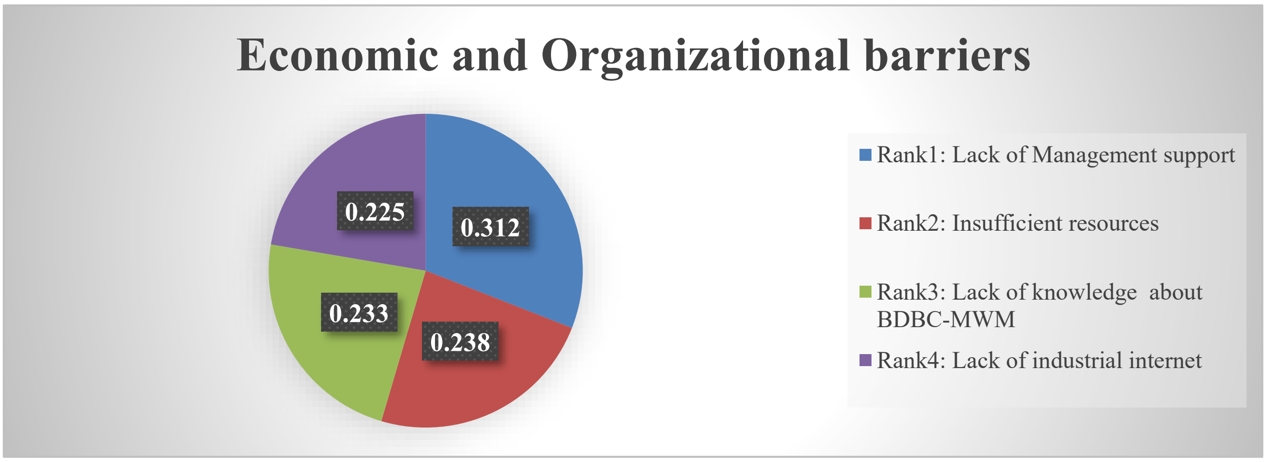

Figure 9. Economic and Government Barriers.

The technological barriers are ranked 4th, with a weight of 0.195. The most significant barrier is regarded as inadequate technological infrastructure (TB1), which is rated 6th with a weight of 0.0735. The next challenges are a lack of information (TB2) and Data security issues (TB3) (shown in Table 16 and Figure 10), which also imply that the integrity of the data on MWM requires secure systems. The implementation of BC and BD technologies is an efficient approach to addressing such issues, as it can provide a secure and transparent platform for waste disposal management, thereby tackling the problems of security and accountability.

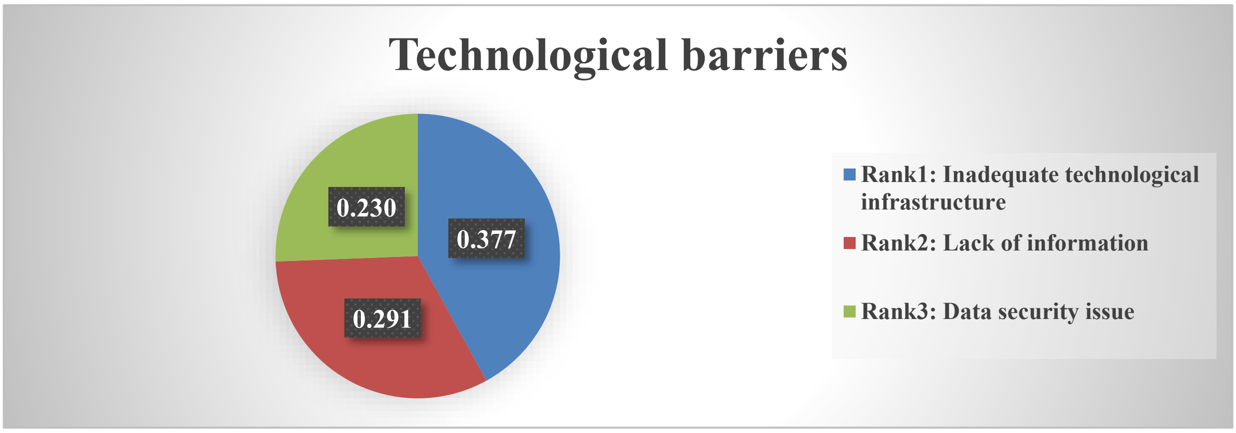

Figure 10. Technological Barriers.

In the final step, the value of global priority was calculated as the product of local priority and the priority order assigned to the category. The following are the key barriers that present the most formidable challenge for some of the major issues that affect BDBC-MWM adoption Lack of research and development units (GB1), Lack of training and education of staff (HB1), Lack of Management support (EOB1), Lack of rules, regulations, and policies (GB3), Lack of international cooperation (GB2), and Inadequate technological infrastructure (TB1). In summary, the weight and ranking of barriers are presented in Table 16. To overcome these obstacles, a combination of BD and the use of BC technology should be employed. The BD is also critical in breaking the management support and knowledge gaps by offering real-time monitoring, predictive analytics, and data-driven insights that can be used to optimize the process of MWM [63]. For example, hospitals can enhance waste collection efficiency, reduce operational costs, and achieve more efficient waste disposal by analyzing large amounts of waste data [64]. There is also an opportunity to develop a comprehensive knowledge base with the help of BD tools, which will reduce the lack of awareness and encourage the adoption of innovative waste management solutions. Conversely, BC supports the issue of data protection and regulatory standards by providing irrevocable and transparent data on waste disposal [65]. It is especially vital in MWM, where the quality of data is crucial for regulatory compliance and the proper monitoring of the source-to-disposal process of medical waste [66]. Cross-border collaboration may also be achieved through BC via the international waste tracking system, which is transparent and secure. It may play a crucial role in countries collaborating to manage global waste flows, including MW [67]. Moreover, compliance with local and international regulations can be automated by applying smart contracts to BC systems, making it more straightforward to ensure that practices for managing medical waste are standardized and transparent across borders [68]. Although the technological infrastructure (TB1) is a notable issue, BC technologies could assist in overcoming these problems and building affordable, decentralized systems that are not based on centralized servers, thereby reducing the need for significant investments in physical infrastructure [69]. The problems of data security are also addressed through decentralization, as data stored using cryptographic algorithms and distributed ledgers is guaranteed to be tamper-proof and inaccessible to unauthorized individuals [70].

To summarize, our findings suggest that, although government barriers and human resource challenges are the most pressing concerns regarding the use of BDBC-MWM, integrating these technologies presents significant opportunities to overcome these challenges. BD can help in making informed decisions, improving waste handling, and sharing knowledge, whereas BC can guarantee secure, transparent, and compliant waste tracking. Addressing the given barriers with the help of strategic investments in technology, workforce training, and policy development will enable the adoption of BDBC-MWM, making it more sustainable and efficient in managing medical waste.

6. Conclusion

We aimed to develop a resilient model to identify the contributory barriers of BC, BD technologies in the sustainable MWM in metropolitan cities. The ISM-MICMAC and AHP analyses were employed to model the magnitude and definition of inter-correlations for 15 barriers, validating these models through expert judgments and a literature review. ISM results revealed insufficient resources, a lack of rules, regulations, and policies, inadequate management, and a lack of industry involvement and collaboration as significant barriers with higher driving power in the adoption of BDBC-MWM practices. MICMAC analysis further identified barriers with the highest driving power, recommending that hospitals/healthcare centers in metropolitan cities focus on financial investments, technological infrastructure, policy development, and industry collaboration for successful technology adoption. The literature has also highlighted the relationship between BDBC-MWM and the existence of these key barriers [7,10,30,36,42,43,45,46]. In contrast, AHP results revealed that government, human, and economic barriers are the key barriers, with high weightage and ranking. This study highlights the significance of BD and BC technologies in MWM as key drivers of sustainability. BD helps hospitals optimize their waste collection time and reduce waste generation with increased efficiencies, resulting in an overall minimized environmental footprint. BC also provides secure, transparent, and immutable waste transaction records for accountability, traceability, and compliance with local and international regulations. These innovative technology pairings enable hospitals to surpass operational targets in line with broader ambitions for environmental resiliency.

This study stimulates academic research on the combination of BC and BD technologies in MWMMWM, with a particular focus on operational and structural challenges. The application of ISM-MICMAC and AHP methods provides a new approach to modeling these barriers, which may be applied to other sectoral or regional research. From a practical viewpoint, these results offer significant implications for healthcare managers and policymakers regarding the investment in technological systems, financial resources, and industry collaborations. These technologies help organizations become more operationally efficient and environmentally sustainable, while ensuring compliance. Cross-sectoral collaboration is necessary to address barriers and optimize the uptake of these technologies in urban healthcare facilities.

6.1. Theoretical implications

By applying an integrated empirical method, we aimed to enhance the understanding of BDBC-MWM barriers by examining their influences and relationships with one another. This study makes new theoretical contributions by shedding light on the broader landscape of healthcare waste and its consequences. The findings provide a more nuanced understanding of various types of healthcare waste and lay the groundwork for future empirical research to formulate hypotheses using reliable and valid variables [70]. This research suggests that BDBC-MWM and contextualized interrelationships are crucial for effective MWM practices, particularly in metropolitan hospital settings. The multi-integrated technique supported us in expanding our understanding of the contextual interdependencies between BDBC-MWM and their impact on the practical implementation of proper MWM practices.

We conducted a study by expert opinions and literature review to identify 15 BDBC-MWM barriers at the first stage. Additionally, we shifted the ISM results to MICMAC analysis to check the dependence and driving powers of BDBC-MWM, and then we applied AHP. The ISM results have shown the top dependence and driving power of insufficient resources and the lack of rules, regulations, and policies. These barriers have a significant impact on other barriers and hinge on BD, BC, and MWM performance. AHP results have shown that Government and Human Barriers are ranked highly due to their weight. These findings indicate that these are key barriers influencing the adoption of BDBC in MWM. Therefore, our research suggests that the location of the effect of direction on each other is diverse, and barriers with strong driving power and high weight require significant consideration in MWM practices.

6.2. Practical implications

This study highlights the challenges in MWM for healthcare globally and the multidimensional nature of these challenges in achieving BDBC-MWM within hospitals and healthcare centers. It also suggests that various barriers influence the effective implementation of BDBC-MWM in hospitals and healthcare centers in metropolitan cities. The barriers with high driving powers in sections 3 and 4 (independent) require a high level of attention. These factors have a significant influence and will drive other related factors that could be substantial obstacles to the successful implementation of BDBC-MWM in the hospital. The practical implications of this study are provided for healthcare administrators, policymakers, and industry stakeholders involved in MWM. The integration of BD and BC technologies can efficiently help process hospital waste, reduce the amount of refuse produced, and enhance data security and regulatory compliance, particularly in metropolitan hospitals with complex waste disposal systems. Yet, deploying these technologies demands massive investment in technical infrastructure and training staff. Hospitals must ensure that employees are well-trained in handling data, tracking waste, and managing sensitive medical records with respect. The study reveals critical challenges for successful incorporation, namely a lack of R&D cells, policy gaps, and inactive management, that need to be addressed to ensure the efficient integration of these technologies. Setting up a specialized research department for waste resource innovation and developing supporting policies is essential. Additionally, cross-sector collaboration requires regulators and government agencies to work across sectors to build the tools and frameworks necessary for facilitating adoption. Furthermore, BD and BC enhance environmental sustainability through efficient waste management, improved disposal processes, and enhanced traceability. An integrated strategy that incorporates technological solutions and sustainable resource management can help minimize the environmental impact caused by medical waste. Healthcare institutions must focus on solutions that not only increase system productivity but also maintain regulatory and environmental compliance, as well as the viability of healthcare systems. To summarize, a holistic approach to MWM should be implemented in hospitals and medical centers, incorporating technological innovations, resource optimization, and sustainable practices. Through this, they will be able to minimize their environmental impact, ensure compliance with regulations, and enhance the sustainability of their practices, thereby paving the way for more environmentally friendly healthcare systems.

6.3. Contribution, limitation, and future research

This research contributes novel literature in BC, BD, and MWM by revealing and advocating a list of tested barriers and ranking them from expert judgments. Professional and academic experts employ the ISM and AHP structural techniques to explore their relationships. We identified two strategic visions for healthcare and MWM in the studied hospitals: One focused on long-term planning and implementation of waste management programs, and the other on coping with specific and unforeseen events when adopting BC and BD. Although this study is significant, there are some limitations. The barriers were identified through surveys and brainstorming sessions conducted exclusively within the Pakistani healthcare arena; therefore, their applicability to other countries may not be generalized. This study offers insights that academics and practitioners can utilize to inform future research on BC, BD, and MWM. On the academic side, researchers could focus on testing the proposed model in a range of healthcare systems to confirm the validity of the relationships between barriers and outcomes, using Structural Equation Modeling (SEM). It could also outline the interdisciplinary nature of BC, BD integration within any healthcare system. On the practical side, the study emphasizes the urgent need to develop and implement cost-effective solutions that address various barriers, including staff training, research and development gaps, and limited regulatory frameworks. As a result, academics offer opportunities for further research to practitioners that will guide the development of the infrastructure. Additional research in the same area enables researchers to replicate studies in other parts of the world, providing sustainable solutions that address the needs of local areas and align with global objectives.

Author Contributions

Muhammad Ismail: Conceptualization, formal analysis, investigation; methodology; supervision & project administration; writing—review and editing; Zhongdong Xiao: Supervision & Project administration; writing—original draft preparation; writing—review and editing; Abdul Waheed: Conceptualization, formal analysis, methodology, software, supervision & project administration, writing—original draft preparation, writing—review and editing; Asifa Iqbal: Conceptualization, Investigation, writing—review and editing; El-Sayed M. El-Kenawy: Formal analysis, methodology, resources; writing—review and editing; Amel Ali Alhussan: Conceptualization, resources, writing—review and editing; Marwa M. Eid: Conceptualization, software, writing—review and editing; Doaa Sami Khafaga: Conceptualization, resources, supervision & project administration.

Use of Generative-AI tools declaration

The authors declare that they have not used AI tools in the creation of this article.

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Data Availability Statement

The data supporting the current study are available within the manuscript.

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Ethical Statement

The concerned authorities approved the questionnaire and methodology of the current study. The present study was approved by the Institutional Review Board (IRB) of the School of Business at Xian International University and was conducted in accordance with the Helsinki ethical standards.

Conflicts of interest

There is no conflict of interest among the authors.

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