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Strategic Assessment of IoT Technologies in Healthcare: Grey MCDM Approach

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ABSTRACT

The integration of Internet of Things (IoT) technologies in healthcare has revolutionized patient monitoring, data analytics, and remote medical device management, significantly improving healthcare delivery. However, selecting the most appropriate IoT technologies in the healthcare sector involves evaluating multiple criteria under conditions of uncertainty. This study addresses this challenge by utilizing the Grey Decision-Making Trial and Evaluation Laboratory (Grey DEMATEL) method to analyze the key criteria influencing IoT technology selection in healthcare. Eight critical criteria, including security, data privacy, technical performance, usability, scalability, and economic factors, were identified and examined for their causal relationships. The results show that security and data privacy are the most influential factors, followed by technical performance and usability. The findings offer valuable insights for decision-makers, assisting them in prioritizing crucial aspects for successful IoT implementation in healthcare. This research contributes to the field by providing a structured decision-making framework that enhances the effective integration of IoT technologies while addressing security, efficiency, and regulatory concerns.

1. Introduction

The Internet of Things (IoT) is a major transformation in the healthcare industry as a technology that enables interconnected devices to exchange data over the internet. In recent years, IoT applications have revolutionized healthcare, with significant improvements in areas such as patient tracking, data analytics, and remote management of medical devices Smart health devices, wearable technology products, sensors, and other IoT-based systems collect and analyze patients' health data and provide instant data to healthcare professionals, helping them make the right decisions. These technologies have great potential, especially in remote patient monitoring, early diagnosis of diseases, improvement of treatment processes, and effective use of resources [1,2].

The aim of this study is to examine how to use Grey MCDM methods in selecting appropriate IoT technologies for remote patient monitoring and data analytics in the healthcare industry. In

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particular, the selection of IoT systems that collect and analyze patients' health data and allow managers/healthcare professionals to make the right decisions is the focus of this study. Grey MCDM methods allow different alternatives to be evaluated over a large number of complex and uncertain criteria, which is an important tool in determining the most suitable IoT technology for the healthcare industry.

The integration of IoT technologies into healthcare significantly increases both efficiency and the quality of patient care. These technologies provide healthcare professionals with the ability to make more accurate, fast and data-driven decisions, while reducing treatment costs by improving the care processes of patients. Remote patient monitoring and data analytics provided by IoT provide more continuous and uninterrupted data on patients' health status, thus contributing to making healthcare faster, more efficient, and effective [3,4]. However, the integration of these technologies into healthcare requires the consideration of many different factors. It increases the importance of this study by revealing how the Grey MCDM method contributes to this multi-criterion decision-making process and how to choose the most appropriate IoT technologies for the healthcare industry.

This article is structured as follows: Section 2 (Literature Review) Previous studies on decision-making processes with the use of IoT in the healthcare sector will be examined. Section 3 (Method) The Grey MCDM method will be introduced, and the evaluation criteria to be used in the study will be determined. Section 4 the process of evaluating IoT technologies with Grey MCDM over the determined criteria will be discussed. Section 5 the study findings will be discussed and practical recommendations will be presented for the integration of IoT technologies into the healthcare sector. In addition, directions for future research will be indicated.

2. Literature review

The integration of IoT and MCDM techniques is of great interest, especially in the fields of healthcare and environmental management. These approaches improve decision-making processes and optimize resource utilization by providing data-driven insights. This literature review synthesizes current studies addressing the applications of IoT and fuzzy MCDM methods in areas such as healthcare, water management, waste management, and high-risk environments.

2.1. IoT and MCDM in healthcare

The healthcare sector is increasingly adopting IoT-based solutions for patient monitoring, telemedicine, and secure data management. Numerous studies have examined the role of MCDM techniques in improving decision-making processes in healthcare systems.

Pant *et al.,* [5] utilized the Analytic Hierarchy Process (AHP) method to prioritize health management practices in smart healthcare systems. In the study, "mental calmness" was identified as the most critical criterion, while "raising awareness" was considered the least important criterion. Additionally, healthy eating was emphasized as being more important than exercise in weight management.

Zaidan *et al.,* [6] proposed a secure decision-making approach for IoT-based healthcare systems using blockchain. In the study, security and privacy requirements were prioritized using the Weighted Zero Inconsistency (FWZIC) and Interval-valued fuzzy global sets (IvSFS) methods. This model optimized security frameworks by making the decision-making processes more robust.

Wahab *et al.,* [7] developed a framework by combining SWOT analysis with fuzzy MCDM techniques to evaluate telemedicine applications in Malaysia. The study highlighted that government support is a critical factor in strengthening telemedicine networks and presented strategies to enhance service quality.

Alamoodi *et al.,* [8] developed a hospital selection framework for patients with multiple chronic diseases using IoT-based wearable sensors. In the study, hospitals were ranked based on various criteria, and "arrival time" was determined to be the most influential factor.

Khan *et al.,* [9] developed a model to evaluate the authentication of Internet of Medical Things (IoMT) devices. The study combined AHP and TOPSIS methods to evaluate security features, strengthening IoT security.

In addition to the healthcare sector, IoT and fuzzy MCDM methods are widely applied in solving environmental issues such as water and waste management.

Narang *et al.,* [10] examined the role of IoT in open-loop water resource management. In the study, the fuzzy DEMATEL method was used to identify the key factors driving IoT adoption in water management. Key factors such as ecosystem configuration, network adaptation, and data mobility were highlighted. The study provides valuable insights for policymakers and businesses regarding sustainable water management.

Rafiquee and Shabbiruddin [11] evaluated waste management systems in Patna, India, using fuzzy logic-based MCDM models. The study concluded that IoT-based door-to-door waste collection systems were the most efficient method. Additionally, "community acceptance" was identified as the most effective criterion, emphasizing the importance of community involvement in waste management strategies.

He *et al.,* [12] examined the applications and challenges of IoT in high-risk environments. The study assessed how IoT-based solutions improved safety measures in industries dealing with environmental, health, and safety (EHS) issues. For this, a q-rung orthopair fuzzy approach (q-ROF-ERSWIA-WASPAS) was developed and used in risk analysis.

This literature review shows that IoT and fuzzy MCDM methods are becoming increasingly effective in healthcare and environmental management fields. In healthcare, these approaches improve patient monitoring, telemedicine, and data security, while in environmental management, they optimize water and waste management applications. Future research should focus on integrating real-time IoT analytics with advanced fuzzy MCDM models, thus enhancing the accuracy and efficiency of decision-making processes. Additionally, addressing cybersecurity threats and improving data-driven decision frameworks will be crucial for maximizing the potential of IoT-based solutions.

2.2. Studies on the grey DEMATEL method

The concept of decision-making models and frameworks has been widely explored across various industries to promote sustainability, optimize operations, and improve organizational performance. These models, particularly the Grey DEMATEL, Analytic Network Process (ANP), and Interpretative Structural Modeling (ISM), have been utilized in numerous studies to tackle complex issues related to supply chain management, resource optimization, waste reduction, and the adoption of new technologies, such as Industry 4.0 and Industry 5.0, and circular economy approaches.

The Grey-DEMATEL approach has been applied to explore enablers of Industry 5.0 (I5.0) for small and medium-sized enterprises (SMEs) in emerging economies. Hsu *et al.,* [13] emphasize the importance of socio-economic-environmental sustainability in supply chains through I5.0, highlighting key enablers like resource availability, management support, government support, and robotic systems for human-robot collaboration. This study is particularly important as it fills a gap in the literature regarding the application of I5.0 in SMEs, which play a crucial role in developing economies. The study integrates MCDM techniques like Fuzzy Delphi and Grey-DEMATEL to identify and rank enablers for SMEs, aiding decision-makers in systematic evaluations and making informed choices to implement sustainability in supply chains.

Another domain where Grey-DEMATEL is applied is Green Public Procurement (GPP), specifically in the Greek public sector. Orfanidou *et al.,* [14] use Grey DEMATEL to explore critical factors that contribute to successful GPP implementation. Their findings provide insight into factors like policy execution and collaboration, which are critical for public organizations in achieving green procurement goals. The research identifies fourteen critical factors, divided into causes and effects, and outlines their influence on the successful implementation of green procurement strategies.

In the agri-fresh produce industry, Anand *et al.,* [15] explore barriers to implementing collaborative practices aimed at reducing food waste and improving sustainability in supply chains. Using Grey-DEMATEL and ANP, the study categorizes barriers into seven dimensions, identifying key challenges in relationship management, economic practices, information sharing, and technological barriers. This framework helps stakeholders understand interrelationships among barriers and prioritize strategies for effective waste minimization and supply chain sustainability.

Humanitarian supply chains (HSCs) also benefit from the Grey-DEMATEL method. Zekhnini *et al.,* [16] investigate the relationship between Industry 4.0 enablers such as Big Data, RFID, IoT, Blockchain, and AI in enhancing the performance of humanitarian supply chains. Their study applies a Grey-DEMATEL-ISM hybrid framework to identify the critical enablers impacting HSC resilience and agility, thus improving humanitarian relief operations during disasters.

The circular economy framework is crucial for managing end-of-life (EOL) solar photovoltaic e-waste. Gautam *et al.,* [17] explore challenges and inhibitors to implementing circular economy strategies in the Indian context, specifically regarding solar photovoltaics. They use Grey-DEMATEL to map causal relationships among 18 key inhibitors, providing insight into the factors hindering the successful implementation of recycling and e-waste management strategies in India's solar energy sector.

Dwivedi *et al.,* [18] investigate the critical success factors (CSFs) for integrating digital technologies with circular supply chains (CSCs). Through Grey-DEMATEL, they identify organizational commitment, technology adoption, and top-management support as the key CSFs that can enable the effective integration of digital technologies in enhancing CSC processes, contributing to sustainable development goals (SDGs).

In the context of metallurgical enterprises, Yan *et al.,* [19] focus on the use of Grey-DEMATEL/ISM to identify safety risk factors in these high-risk environments. Their study clarifies the relationships between accident-causing factors and proposes an early-warning system based on a Bayesian network model, which integrates causal relationships among risk factors and provides actionable insights for improving safety and minimizing accidents.

Li *et al.,* [20] present a multi-index evaluation model for assessing risks to trainees in emergency rescue training for building collapse situations. They use an improved Grey-DEMATEL-ISM-MICMAC model to evaluate risk levels and prioritize safety measures. The results highlight the importance of safety education, operating standards, and equipment inspection, offering insights into how to mitigate risks in training scenarios for better preparedness in real-life emergencies.

The shift to online education during the COVID-19 pandemic has led to increased academic burnout among students. Aria *et al.,* [21] apply Grey Delphi and Grey-DEMATEL techniques to identify the factors affecting student burnout in online learning environments. They categorize influencing factors such as technology infrastructure, institutional facilities, and faculty characteristics, helping policymakers focus on these key areas to prevent burnout and improve online education experiences.

Li *et al.,* [22] explore the phenomenon of greenwashing among construction materials enterprises in China. Using the Grey-DEMATEL method, they identify and analyze factors influencing greenwashing behaviors, such as corporate social performance, information transparency, and market environment. The study offers a unique perspective on how multi-agent interactions shape greenwashing behaviors, contributing to a broader understanding of corporate environmental practices.

The literature reveals a wide array of applications of Grey-DEMATEL and related MCDM techniques in addressing complex issues in sustainability, supply chain management, risk assessment, and technology adoption across various sectors. These studies contribute to a deeper understanding of how causal relationships can be identified and analyzed, assisting stakeholders in making informed, strategic decisions to improve operational efficiency, reduce risks, and promote sustainable practices.

3. Methodology

In this study, Grey MCDM will be used to evaluate IoT technologies in the healthcare sector. The Grey DEMATEL method is used to determine the relationships between criteria in complex and ambiguous decision-making processes. Grey DEMATEL, a variant of Grey MCDM, is particularly suitable for dealing with ambiguous and incomplete data. In this study, the Grey DEMATEL method will be used to determine how to rank and evaluate various features of IoT technologies according to the specified criteria.

3.1 Evaluation criteria

In this study, the main criteria to be considered in the evaluation of IoT technologies in the health sector are given in Table 1.

Table 1
Evaluation criteria

Code	Criteria	Description
C1	Environmental Impact	The impact of IoT technologies on the environment, including factors such as energy consumption, resource usage, and the integration of environmentally friendly technologies.
C2	Scalability	The ability of IoT technologies to adapt to a growing healthcare network and an increasing number of patients, focusing on the scalability of the system.
C3	Usability and User Experience	How easy and efficient the technologies are for healthcare professionals and patients to use, whether the devices are user-friendly, and the quality of system interfaces.
C4	Economic Factors	The cost-effectiveness of IoT technologies, return on investment (ROI), initial costs, maintenance costs, and long-term economic sustainability.
C5	Security and Data Privacy	The security features of IoT devices, the protection of patients' personal health data, compliance with data security standards, and privacy factors.
C6	Technical Performance	The efficiency, processing speed, accuracy of devices, system compatibility, network capacity, and technical reliability of IoT technologies.
C7	Compatibility and Integration	The capacity of IoT systems to work in harmony with existing healthcare infrastructure and other technologies, including data integration and seamless communication.
C8	Legal Compliance and Ethics	The compliance of IoT technologies with legal regulations and ethical standards in the healthcare sector, respecting patient rights, and ensuring healthcare services are provided within a legal framework.

These criteria in Table 1 will be analyzed with the Grey DEMATEL method to determine the most effective and critical criteria and will help make strategic decisions for the successful implementation of IoT technologies in the healthcare sector.

3.2. Grey system theory

The grey system theory was proposed by Deng [23] to solve uncertainties in situations involving discrete data and incomplete information. Grey system analysis is carried out with grey numbers, grey equations and/or grey matrices [24]. When it comes to grey numbers, neither black nor white concepts may come to mind once in a while, their values cannot be clearly expressed in numbers, but they are known to take values in which range. Grey number is $(\otimes x)$, $\otimes x \in [\underline{\otimes} x, \overline{\otimes} x]$ with x being a real number where, $\underline{\otimes} x$ and $\overline{\otimes} x$ refer to the lower and upper limits of the number of $\otimes x$ greys, respectively. $\otimes x_1$ and $\otimes x_2$ are used for basic operations that can be done with grey numbers.

$$\otimes x_1 + \otimes x_2 = \left[\underline{x_1} + \underline{x_2}, \overline{x_1} + \overline{x_2}\right] \tag{1}$$

$$\otimes x_1 - \otimes x_2 = \left[\underline{x_1} - \overline{x_2}, \overline{x_1} - \underline{x_2}\right] \tag{2}$$

$$\otimes x_1 . \otimes x_2 = \left[\min\left(\underline{x_1}.\underline{x_2}, \underline{x_1}.\overline{x_2}, \overline{x_1}.\underline{x_2}, \overline{x_1}.\overline{x_2}\right), max\left(\underline{x_1}.\underline{x_2}, \underline{x_1}.\overline{x_2}, \overline{x_1}.\underline{x_2}, \overline{x_1}.\overline{x_2}\right)\right] \tag{3}$$

$$\otimes x_1 : \otimes x_2 = \left[\underline{x_1}, \overline{x_1}\right].\left[\frac{1}{\underline{x_2}}, \frac{1}{\overline{x_2}}\right] \tag{4}$$

$$k \in \mathcal{R}^+, k.\otimes x = \left[k.\underline{x}, k.\overline{x}\right] \tag{5}$$

3.3. Grey DEMATEL Yöntemi

The process steps of the Grey DEMATEL method, which is integrated with grey numbers for criterion weighting, are given below [25,26].

Each decision maker determines the effect of the binary comparisons on each other with “0= no influence, 1= very low influence, 2= low influence, 3= high influence, and 4= very high influence”. At this stage, the effects of the verbal expressions of these decision-makers are converted into numerical values consisting of grey numbers according to the gray linguistic terms scale shown in Table 2.

Table 2
Linguistic terms and grey numbers [27]

Linguistic Terms	Grey Numbers
No influence (N)	[0, 0]
Very low influence (VL)	[0, 1]
Low influence (L)	[1, 2]
High influence (H)	[2, 3]
Very high influence (VH)	[3, 4]

The grey direct relationship matrices generated by the k decision maker is indicated by Eq. (6).

$$Z^k = \begin{bmatrix} [0,0] & \otimes z_{12}^k & \dots & \otimes z_{1n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \otimes z_{1n}^k & \otimes z_{2n}^k & \dots & [0,0] \end{bmatrix} \tag{6}$$

The combined grey direct relationship matrix (Z) is obtained by averaging all the resulting grey direct relationship matrices. Eqs. (7)-(9) is used to obtain a normalized combined grey direct relationship matrix.

$$\otimes S = [\underline{S}, \overline{S}] = \frac{1}{\max\limits_{1 \le i \le n} \sum_{j=1}^{n} \otimes z_{ij}}, \;\; i,j = 1, \dots, n \tag{7}$$

$$\otimes N = \otimes S.Z \tag{8}$$

$$\otimes n_{ij} = \left[\underline{s}.\underline{z_{ij}}, \overline{s}.\overline{z_{ij}}\right] \tag{9}$$

A total relationship matrix is created using Eqs. (10)-(12).

$$\otimes T = N + N^2 + N^3 + \cdots = \sum_{i=1}^{\infty} N^i = N(I - N)^{-1} \tag{10}$$

$$\otimes \underline{T} = \underline{N}\left(I - \underline{N}\right)^{-1} \tag{11}$$

$$\otimes \overline{T} = \overline{N}\left(I - \overline{N}\right)^{-1} \tag{12}$$

Using Eqs. (13) and (14), the row ⊗R and column ⊗C totals of the total relationship matrix are obtained.

$$\otimes R_i = \sum_{j=1}^{n} \otimes t_{ij} \tag{13}$$

$$\otimes C_j = \sum_{i=1}^{n} \otimes t_{ij} \tag{14}$$

Eqs. (115) and (16) are used for criterion weights.

$$\omega_i = \sqrt{(R_i + C_i)^2 + (R_i - C_i)^2} \tag{15}$$

$$w_i = \frac{\omega_i}{\sum_{i=1}^{n} \omega_i} \tag{16}$$

4. Empirical analysis and results

This section presents the empirical analysis conducted using the Grey DEMATEL method to evaluate IoT technologies in the healthcare sector. The Grey DEMATEL method identifies causal relationships between criteria, allowing the analysis of which criteria are more influential in the decision-making process.

The analysis conducted within this study consists of the following steps:

i. Data Collection: Expert opinions were gathered to determine the relationships between criteria. Based on previous studies in the literature and expert evaluations, Grey numbers were used to define the interactions between criteria.
ii. Formation of the Initial Direct Relationship Matrix: Direct effects between criteria were identified based on expert evaluations, and a relationship matrix was constructed.
iii. Grey Normalized Relationship Matrix: The initial direct relationship matrix was normalized to scale the relationships between criteria.
iv. Calculation of the Total Influence Matrix: Using the normalized matrix, the total influence matrix was computed, and the total influence values between criteria were obtained.
v. Cause-and-Effect Analysis of Criteria: With the Grey DEMATEL method, criteria were classified as cause factors (which influence other criteria) and effect factors (which are influenced by other criteria).
vi. Identification of Critical Criteria: By analyzing the relationships between criteria, the most decisive factors in the evaluation of IoT technologies were determined.

4.1. Gray DEMATEL method application results

By using three different expert opinions separately, gray direct relationship matrices were created for each of the three experts using Eq. (6) with the grey numbers in Table 2. These matrices are given in Tables 3-5.

Table 3
Grey direct relationship matrix for Expert-1

Criteria	C1	C2	C3	C4	C5	C6	C7	C8
C1	[0,0]	[1,2]	[1,2]	[1,2]	[2,3]	[0,1]	[0,1]	[0,1]
C2	[0,1]	[0,0]	[0,1]	[2,3]	[2,3]	[2,3]	[1,2]	[0,1]
C3	[3,4]	[2,3]	[0,0]	[2,3]	[3,4]	[2,3]	[1,2]	[1,2]
C4	[1,2]	[2,3]	[2,3]	[0,0]	[2,3]	[1,2]	[0,1]	[0,1]
C5	[2,3]	[3,4]	[0,1]	[2,3]	[0,0]	[3,4]	[3,4]	[0,1]
C6	[2,3]	[0,1]	[1,2]	[2,3]	[3,4]	[0,0]	[3,4]	[3,4]
C7	[0,1]	[0,1]	[1,2]	[0,1]	[0,1]	[0,1]	[0,0]	[2,3]
C8	[0,1]	[0,1]	[0,1]	[3,4]	[0,1]	[0,1]	[3,4]	[0,0]

Table 4
Grey direct relationship matrix for Expert-2

Criteria	C1	C2	C3	C4	C5	C6	C7	C8
C1	[0,0]	[1,2]	[1,2]	[1,2]	[3,4]	[2,3]	[0,1]	[0,1]
C2	[1,2]	[0,0]	[0,1]	[2,3]	[1,2]	[3,4]	[0,1]	[0,1]
C3	[3,4]	[2,3]	[0,0]	[2,3]	[2,3]	[0,1]	[0,1]	[0,1]
C4	[0,1]	[2,3]	[2,3]	[0,0]	[1,2]	[1,2]	[1,2]	[0,1]
C5	[1,2]	[3,4]	[0,1]	[2,3]	[0,0]	[3,4]	[1,2]	[2,3]
C6	[0,1]	[0,1]	[1,2]	[2,3]	[3,4]	[0,0]	[2,3]	[0,1]
C7	[1,2]	[0,1]	[1,2]	[0,1]	[1,2]	[0,1]	[0,0]	[0,1]
C8	[1,2]	[0,1]	[0,1]	[3,4]	[1,2]	[2,3]	[2,3]	[0,0]

Table 5
Grey direct relationship matrix for Expert-3

Criteria	C1	C2	C3	C4	C5	C6	C7	C8
C1	[0,0]	[1,2]	[3,4]	[1,2]	[0,1]	[1,2]	[1,2]	[2,3]
C2	[1,2]	[0,0]	[1,2]	[2,3]	[1,2]	[0,1]	[1,2]	[2,3]
C3	[3,4]	[2,3]	[0,0]	[3,4]	[2,3]	[2,3]	[3,4]	[1,2]
C4	[0,1]	[0,1]	[0,1]	[0,0]	[1,2]	[1,2]	[1,2]	[2,3]
C5	[2,3]	[2,3]	[1,2]	[1,2]	[0,0]	[1,2]	[3,4]	[2,3]
C6	[2,3]	[1,2]	[1,2]	[1,2]	[1,2]	[0,0]	[3,4]	[3,4]
C7	[2,3]	[2,3]	[0,1]	[1,2]	[3,4]	[1,2]	[0,0]	[0,1]
C8	[3,4]	[1,2]	[0,1]	[1,2]	[1,2]	[2,3]	[2,3]	[0,0]

The combined grey direct relationship matrix, which is obtained by averaging the grey direct relationship matrices created by experts, is given in Table 6.

Table 6
Combined gray direct relationship Matrix

Criteria	C1	C2	C3	C4	C5
C1	[0.000,0.000]	[0.667,1.667]	[2.000,3.000]	[0.667,1.667]	[1.667,2.667]
C2	[0.667,1.667]	[0.000,0.000]	[0.667,1.667]	[1.667,2.667]	[1.333,2.333]
C3	[3.000.4.000]	[2.000,3.000]	[0.000,0.000]	[1.667,2.667]	[2.333,3.333]
C4	[0.333,1.333]	[1.000,2.000]	[1.667,2.667]	[0.000,0.000]	[1.333,2.333]
C5	[1.667,2.667]	[2.333,3.333]	[0.333,1.333]	[1.333,2.667]	[0.000,0.000]
C6	[1.333,2.333]	[0.333,1.333]	[1.333,2.333]	[1.333,2.333]	[2.333,3.333]
C7	[1.000,2.000]	[0.667,1.667]	[0.333,1.333]	[0.667,1.667]	[1.333,2.333]
C8	[1.333,2.333]	[1.000,2.000]	[0.000,1.000]	[1.667,2.667]	[0.667,1.667]

Table 6
Continued

Criteria	C6	C7	C8
C1	[1.000,2.000]	[0.333,1.333]	[0.667,1.667]
C2	[1.667,2.667]	[0.667,1.667]	[0.667,1.667]
C3	[1.333,2.333]	[1.333,2.333]	[0.667,1.667]
C4	[1.000,2.000]	[0.667,1.667]	[0.667,1.667]
C5	[2.333,3.333]	[2.333,3.333]	[1.333,2.333]
C6	[0.000,0.000]	[2.667,3.667]	[2.000,3.000]
C7	[0.333,1.333]	[0.000,0.000]	[0.667,1.667]
C8	[1.333,2.333]	[2.333,3.333]	[0.000,0.000]

The normalized gray direct relationship matrix obtained using Eqs. (7)-(9) is given in Table 7.

Table 7
Normalized grey direct relationship matrix

Criteria	C1	C2	C3	C4	C5
C1	[0.000,0.000]	[0.034,0.086]	[0.103,0.155]	[0.034,0.086]	[0.086,0.138]
C2	[0.034,0.086]	[0.000,0.000]	[0.034,0.086]	[0.086,0.138]	[0.069,0.121]
C3	[0.155,0.207]	[0.103,0.155]	[0.000,0.000]	[0.086,0.138]	[0.121,0.172]
C4	[0.017,0.069]	[0.052,0.103]	[0.086,0.138]	[0.000,0.000]	[0.069,0.121]
C5	[0.086,0.138]	[0.121,0.172]	[0.017,0.069]	[0.069,0.138]	[0.000,0.000]
C6	[0.069,0.121]	[0.017,0.069]	[0.069,0.121]	[0.069,0.121]	[0.121,0.172]
C7	[0.052,0.103]	[0.034,0.086]	[0.017,0.069]	[0.034,0.086]	[0.069,0.121]
C8	[0.069,0.121]	[0.052,0.103]	[0.000,0.052]	[0.086,0.138]	[0.034,0.086]

Criteria	C6	C7	C8
C1	[0.052,0.103]	[0.017,0.069]	[0.034,0.086]
C2	[0.086,0.138]	[0.034,0.086]	[0.034,0.086]
C3	[0.069,0.121]	[0.069,0.121]	[0.034,0.086]
C4	[0.052,0.103]	[0.034,0.086]	[0.034,0.086]
C5	[0.121,0.172]	[0.121,0.172]	[0.069,0.121]
C6	[0.000,0.000]	[0.138,0.190]	[0.103,0.155]
C7	[0.017,0.069]	[0.000,0.000]	[0.034,0.086]
C8	[0.069,0.121]	[0.121,0.172]	[0.000,0.000]

The total relationship matrix obtained using Eqs (10)-(12) is given in Table 8.

Table 8
The total relationship matrix

Criteria	C1	C2	C3	C4	C5
C1	[1.0505,1.4338]	[0.0775,0.4843]	[0.1283,0.4983]	[0.0782,0.5116]	[0.1356,0.5959]
C2	[0.0763,0.5067]	[1.0388,1.4004]	[0.0665,0.4422]	[0.1236,0.5527]	[0.1182,0.5802]
C3	[0.2114,0.7337]	[0.1594,0.6578]	[1.0553,1.4741]	[0.1473,0.6801]	[0.1959,0.7636]
C4	[0.0631,0.4836]	[0.0891,0.4848]	[0.1092,0.4716]	[1.0421,1.4186]	[0.1157,0.5662]
C5	[0.1403,0.6562]	[0.1635,0.6499]	[0.0649,0.5213]	[0.1272,0.6622]	[1.0777,1.5936]
C6	[0.1313,0.6383]	[0.0774,0.5619]	[0.1072,0.5509]	[0.1261,0.6380]	[0.1856,0.7300]
C7	[0.0784,0.4543]	[0.0612,0.4183]	[0.0384,0.3693]	[0.0619,0.4420]	[0.0990,0.5043]
C8	[0.1052,0.5421]	[0.0851,0.5002]	[0.0360,0.4223]	[0.1222,0.5601]	[0.0873,0.5620]

Criteria	C6	C7	C8
C1	[0.0961,0.5214]	[0.0701,0.5242]	[0.0677,0.4504)
C2	[0.1250,0.5470]	[0.0858,0.5385]	[0.0690,0.4516]
C3	[0.1371,0.6624]	[0.1400,0.6978]	[0.0868,0.5608]
C4	[0.0923,0.5072]	[0.0822,0.5238]	[0.0653,0.4386]
C5	[0.1736,0.6831]	[0.1849,0.7248]	[0.1158,0.5754]
C6	[1.0633,1.5240]	[0.2032,0.7312]	[0.1450,0.5936]
C7	[0.0488,0.4247]	[1.0337,1.3850]	[0.0558,0.3913]
C8	[0.1063,0.5399]	[0.1615,0.6168]	[1.0346,1.3793]

Eqs. (13)-(14) is given in Table 9 by obtaining the row and column totals of the total relationship matrix.

Table 9
Row and column totals of the total relationship matrix

Criteria	R	C	R+C	R-C
C1	[0.7040,4.0199]	[0.8564,7.0082]	[1.5605,11.0282]	[-6.3042,3.1635]
C2	[0.7032,4.0202]	[0.7521,6.4990]	[1.4554,10.5193]	[-5.7958,3.2681]
C3	[1.1332,5.2303]	[0.6057,5.6606]	[1.7390,10.8908]	[-4.5273,4.6245]
C4	[0.6590,3.8944]	[0.8285,6.8045]	[1.4875,10.6989]	[-6.1455,3.0659]
C5	[1.0479,5.0667]	[1.0150,7.7759]	[2.0629,12.8426]	[-6.7280,4.0517]
C6	[1.0391,4.9680]	[0.8425,6.6224]	[1.8816,11.5904]	[-5.5833,4.1255]
C7	[0.4772,3.3890]	[0.9615,6.9383]	[1.4387,10.3274]	[-6.4612,2.4276]
C8	[0.7382,4.1225]	[0.6401,5.7839]	[1.3782,9.9064]	[-5.0457,3.4825]

The criterion weights and importance order calculated using Eqs. (15)-(16) are given in Table 10.

Table 10
Criterion weights and importance ranking

Criteria	Weights	Rank
Environmental Impact	0.1249	4
Scalability	0.1188	6
Usability and User Experience	0.1253	3
Economic Factors	0.1209	5
Security and Data Privacy	0.1479	1
Technical Performance	0.1336	2
Compatibility and Integration	0.1167	7
Legal Compliance and Ethics	0.1119	8

The evaluation in Table 10 analyzes the critical criteria of IoT technologies in the healthcare sector using the Grey DEMATEL method. The weights and rankings of the criteria are interpreted below:

Security and Data Privacy (0.1479 - Ranked 1st). This stands out as the most important criterion. In the healthcare sector, protecting patients' personal health data, ensuring resilience against cybersecurity threats, and complying with data privacy standards are the most critical factors. This aligns with the increasing sensitivity of health data and the growing risk of cyberattacks.

Technical Performance (0.1336 - Ranked 2nd). The accuracy, processing speed, connection quality, and overall reliability of IoT systems are fundamental requirements for successful implementation in the healthcare sector. Particularly in applications such as remote patient monitoring and data analytics, technical performance plays a crucial role.

Usability and User Experience (0.1253 - Ranked 3rd). The ease and efficiency with which healthcare professionals and patients can use IoT devices are essential for technology adoption. User-friendly interfaces, intuitive design, and easy accessibility are evaluated under this criterion.

Environmental Impact (0.1249 - Ranked 4th). The energy consumption, carbon footprint, and compatibility of IoT systems with eco-friendly technologies are significant factors in the healthcare sector. However, considering that criteria such as security and technical performance are more critical, this criterion holds a medium level of importance.

Economic Factors (0.1209 - Ranked 5th). The cost-effectiveness, return on investment (ROI), and sustainability of IoT technologies are important for healthcare institutions. However, compared to other technical and security criteria, they hold slightly less importance. Since high costs can be balanced with long-term gains, this criterion is not among the top priorities.

Scalability (0.1188 - Ranked 6th). The ability of IoT technologies to adapt to expanding healthcare services is an important criterion for the future. However, since security, performance, and usability are the primary concerns for existing systems, this criterion ranks lower.

Compatibility and Integration (0.1167 - Ranked 7th). The extent to which IoT systems can integrate with existing hospital infrastructures is crucial for seamless data flow between systems. However, since this criterion is directly linked to user experience and technical performance, it follows them in ranking.

Legal Compliance and Ethics (0.1119 - Ranked 8th). This criterion has the lowest weight. The reason is that IoT technologies can be adapted to legal frameworks after their development, and compared to other factors, they do not directly impact the implementation process. However, this does not mean that ethical and legal regulations are unimportant. Compliance with regulations is essential for long-term sustainability.

Security, technical performance, and user experience have been identified as the most critical factors for IoT technologies in the healthcare sector. Economic and environmental factors hold medium importance and are directly related to the long-term sustainability of technologies. Factors such as legal compliance and integration have not been as decisive as other technical and security factors. However, this does not mean that regulations should be disregarded. These findings help determine the most critical factors for the adoption and implementation of IoT technologies in the healthcare sector and provide decision-makers with a strategic roadmap.

5. Conclusion

This study presents a comprehensive analysis of the evaluation and selection of Internet of Things (IoT) technologies in the healthcare sector using the Grey Multi-Criteria Decision-Making (MCDM) approach, specifically the Grey DEMATEL method. IoT technologies offer significant opportunities in areas such as remote patient monitoring, data analytics, and improving the efficiency of healthcare services. However, integrating these technologies into the healthcare sector requires considering multiple criteria. The eight criteria identified in this study were evaluated based on expert opinions and literature reviews, and their importance levels were determined using the Grey DEMATEL method.

As a result of the analysis, Security and Data Privacy (0.1479) was identified as the most critical criterion. This finding highlights the priority of protecting patients' personal data and ensuring cybersecurity in the healthcare sector. Technical Performance (0.1336) emerged as the second most important criterion, emphasizing the critical role of accuracy, processing speed, and network reliability of IoT systems in healthcare services. Usability and User Experience (0.1253) ranked third, underlining the importance of healthcare professionals and patients being able to use IoT devices effectively. Environmental Impact (0.1249) and Economic Factors (0.1209) were identified as criteria with moderate importance. The energy consumption, sustainability, and cost-effectiveness of IoT systems are essential for the long-term success of the healthcare sector. Scalability (0.1188) is crucial for adapting systems to a growing patient population, but it received a lower weight compared to other factors. Compatibility and Integration (0.1167) and Legal Compliance and Ethics (0.1119) had the lowest weights, but this does not mean these factors should be disregarded. The successful implementation of IoT systems in healthcare requires compliance with legal and ethical regulations.

Based on the findings of this study, the following recommendations are proposed for the successful adoption of IoT technologies in the healthcare sector:

i. Enhancing Security Measures: Strong encryption, access controls, and data anonymization techniques should be used to improve the security of IoT systems. Additionally, healthcare institutions should regularly update their cybersecurity policies.

ii. Optimizing Technical Performance: IoT devices must have high accuracy, fast data processing capacity, and low latency. Healthcare systems should prioritize devices that meet these technical requirements during integration.
iii. Developing User-Friendly Systems: User-friendly interfaces should be designed for both healthcare professionals and patients. Training programs and guides should be provided to ensure users can utilize the systems efficiently.
iv. Considering Environmental and Economic Factors: IoT technologies should be developed with low energy consumption and eco-friendly components. Moreover, cost-effectiveness should be prioritized, and solutions with high return on investment (ROI) should be selected.
v. Adopting Scalable Solutions: IoT systems should be flexible and scalable to meet the increasing demands of the healthcare sector.
vi. Ensuring Compliance with Legal Regulations: IoT systems should seamlessly integrate with existing healthcare infrastructures and comply with legal frameworks. Patient privacy, ethical guidelines, and national/international regulations should be considered.

Although this study provides significant insights into the evaluation of IoT technologies in healthcare, it also suggests potential areas for future research:

i. Comparison of Different MCDM Methods: Comparative analyses can be conducted using other MCDM methods (e.g., AHP, TOPSIS, ANP) alongside Grey DEMATEL for evaluating IoT technologies.
ii. Applications in Different Healthcare Fields: The effectiveness of IoT technologies in different healthcare areas (e.g., chronic disease management, remote monitoring in emergency services) can be explored.
iii. Utilization of Real-Time Data: New approaches can be developed to improve healthcare services by analyzing real-time data obtained from IoT-based systems.

In conclusion, this study provides a decision support mechanism for evaluating IoT technologies in the healthcare sector and guides healthcare institutions in integrating these technologies more effectively. The Grey DEMATEL method proves to be an effective tool for handling uncertain and complex decision-making processes and offers strategic insights to enhance the quality of healthcare services.

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Conflicts of Interest
The author declares no conflicts of interest.

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