

Article

Innovation Resistance and Resource Allocation Strategy of Medical Information Digitalization

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Abstract: Healthcare industries are facing an enormous flow of medical records due to the progression of information technology and the trend of digital transformation. Thus, medical information digitalization is a huge digital dataset that can be utilized to benefit healthcare systems and patients. While many studies focus on the application of the digitalized medical information in the healthcare field, only a few mentioned its resistance. The theoretical background depicts a comprehensive overview of medical information digitalization and the barriers in previous literature. This study emphasized the interaction of medical information digitalization barriers and applies the importance-resistance analysis model (IRA) to identify the resistant factors overcoming strategy. It also clarifies the pathway to eliminating the innovation resistance and reveals the interaction of medical information digitalization barriers. The acquisition, management, and application of medical information digitalization are the key foundation of medical technology innovation, digital transformation, and the application of artificial intelligence. This work can reduce the limitation of a narrow healthcare context. This study helps healthcare industries to clarify and solve barriers and realizes the innovation and application of medical information digitalization. In the long term, the results provide a basis for the future development direction of medical information digitalization and affect the medical industry.

Keywords: medical information digitalization; innovation resistance; artificial intelligence; healthcare technological innovation; resource allocation



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1. Introduction

Digitalization has become a more and more important aspect in all fields in our lives. Our life and health technologies have been merged with digital transformation and its progression with the usage of variety digital features that are implemented into medical application [1]. Recently, technological progress in healthcare industries has led to advancements in digitalization [2]. The digitalization of medical information could benefit the healthcare system through various aspects. The development in digital information can contribute to sharing and generating knowledge. The data drawn from the large populations can be fed into machine-learning applications to differentiate patterns that can improve the prognostic tools and allow the automation of some diagnostic processes [3].

In the last two decades, information digitalization has become the trend in research and applied science due to its ability to create big impact and values [4,5]. Big data covers

nearly every aspect of our lives. Moreover, it is the basis for fundamental discovery and advances in technologies, such as digital transformation, robotics, and application of artificial intelligence, having allowed for the expansion of information beyond its traditional scope [6]. With the support of different methods and technologies, big data are generally considered as a promising means to provide benefits in terms of analysis beyond human capability, such as in specifying problem areas, analyzing unmet needs, or enhancing value chains [7–9]. Multiple opportunities are associated with leveraging big data; as such, an increasing number of organizations are advocating for the construction of a big data system.

In the medical field, a daily stream of medical data from millions of patients leads to various big data applications in many medical institutions. At present, the generation of medical information digitalization has been acknowledged as a new breakthrough technology that presents a great impact on improving the outcomes of healthcare systems [10–12]. Furthermore, several studies have explored big data development in the healthcare field through bibliometric and visualization approaches [5,13]. Big data technology is one of the largest concerns of medical organizations in their attempt to reduce costs and improve their data management performance [13–15]. However, despite the fact that the number of studies and projects on medical information digitalization has continued to increase, obtaining benefits from healthcare applications is difficult due to numerous barriers [16].

However, the digitization of medical data also faces many challenges, including resource, sharing, integration, analysis, and supervision of data [15,17–19]. Nevertheless, as more and more medical data are collected, the potential of medical information digitalization and digital transformation for improving healthcare and advantages is still huge and can be predicted. Assessing the obstacles that may be encountered and clarifying the impact of different barriers are the key factors for developing medical information digitalization. Therefore, the impact of different barriers on the development of medical information digitalization should be clarified to facilitate the development of medical information digitalization. In addition, the more the data open, the more support that the optimal limited resources could be informed by a range of stakeholders [20]. This study adopts interviews of stakeholders and literature review to establish barriers that affect medical information digitalization innovation and development. This research helps to clarify the ways to improve the barriers in the development of medical information digitalization and to improve on the excellent resource allocation and strategic pathway.

1.1. Literature Review

Through literature review, this research aims to carry out the barriers that affect the realization of the medical information digitalization system in medical institutions.

1.1.1. Medical Information Digitalization

The concept of big data reflects the increasing amount of information, which cannot be accommodated by traditional systems due to inadequate capacity, processing, and analytical ability. The rapid expansion of digital collection and storage space has led to the development of the science of data management and analysis to enable organizations to transform vast amounts of resources into information and knowledge that can help achieve their goals [21]. Big data have been gradually applied in e-commerce [22], tourism [23], industrial production [24], and operations management [25]. In the medical field, the application of medical information digitalization has gained increasing attention.

Medical institutions worldwide are facing an enormous flow of medical records due to the increasing number of patient visits on a daily basis. Medical information digitalization is viewed as comprising a huge digital dataset that can be utilized to improve or benefit healthcare systems and patients [11]. Based on the digital health framework, medical information digitalization can be grouped into three categories: formal care, informal care, and biomedical research [10]. The first and foremost principle is formal care, which is mostly generated in the form of electronic health records that are generally used for keeping patient data, which range from personal information to treatment records and

for providing doctors and therapists the ability to monitor the treatment [26]. The second category is informal care [27]. Several studies suggested that consumers have become a potential data source in healthcare applications, such as personal health records and other information about personal activities that could be related to medical information. The last category is biomedical research [28], which can be reused and related to current studies, thereby integrating and enhancing the speed of study. In general, many studies believe that the appropriate application of medical information digitalization has great potential and advantages in improving health economics, monitoring the security of healthcare systems, and promoting the development of medical technology [29].

1.1.2. Medical Information Digitalization Barriers

Although digitalizing medical information can benefit organizations in different ways, many medical institutions have encountered challenges in implementing a medical data system [30,31]. Therefore, how to adopt, supervise, and apply digital technology is important for governing medical information digitalization effectively, and resistance elimination has become the key to the successful application and economic value of medical information digitalization [16,32]. Medical information digitalization faces a high chance of failure due to various challenges that have been barely investigated in publicized research [33]. For example, to plan an effective medical information digitalization system, hospitals and clinics would need to invest a significant amount for the initial cost in the system infrastructure, ongoing maintenance, storage, and data analysis expense [15,34]. Even when used in operations, the system needs to guarantee adequate competence and eligibility when generating appropriate value or services for users. Developing new systems for constructing medical data in the context of medical institutions is difficult [14,35]. Moreover, uncovered issues to system development are the main causes of difficulties experienced by medical institutions when adopting the system in the first place [36,37]. The current environment surrounding digital capture and storage is under heated debate as healthcare organizations, policy makers, and the legal system try to evolve appropriate structures and safeguards for the protection of patient privacy [38]. Among these inherent situations, the privacy and security of patient information is one of the most crucial factors for reducing patients' willingness to be part of the system. Patients believe that their medical records may be violated by the capability of medical digitalizing data applications in healthcare-wearable devices. Their concern stems from the possibility that their personal information can be leaked out and misused while the medical records are processed [39,40]. In addition, many institutions have not adopted the system for a variety of reasons [34,41]. Apart from the barriers confirmed by previous studies, this research aims to determine specific resistance factors from an organizational perspective. Basing on literature review and expert interviews, this paper categorizes medical information digitalization barriers into five main dimensions: digitalized analysis and process; medical data sharing; infrastructure resources; regulation and constraints; and operational issue.

Digitalized Analysis and Process

The dearth of expertise in digitalization is a problem of paramount importance among medical institutions [15,42]. Such technology would not provide any beneficial outcomes unless medical institutions can analyze the large amounts of data that they generate [43,44]. Hospitals acknowledge the numerous drawbacks they encounter when implementing medical information digitalization technology; the most noticeable of which is the lack of experience [42,45]. Medical institutions that are new to this data-driven system and have no precise implementation strategy suffer from the initial shortcomings of inadequate experience [14]. In other words, small medical institutions usually lack the ability to use and analyze medical information digitalization, leading to inefficient implementation of the system [46]. Data utilization is similarly problematic due to the varying constructions and definitions of medical information digitalization in different medical institutions [43,47]. Healthcare employees who lack competency in utilizing medical information digitalization

may encounter significant difficulties in developing a system for their institutions [48]. Despite the vigor of qualified staff toward the success of medical information digitalization implementation, identifying big data analytic talents is a difficult task [42,49,50].

Medical Data Sharing

The huge quantity of data, which have sizes ranging from terabytes to exabytes and are generated on a daily basis, exceeds the limitations of traditional realization and storage of relational data [43,51]. Therefore, the mass storage system is expected to improve the expansion capability. The implementation of a medical information digitalization system makes controlling metadata that agglomerated at the system layer, which is a painful experience for many medical institutions. The speed of data presentation and retrieval on current medical platforms is another important consideration [50,51]. Different conditions and quality requirements for data application in different clinical departments also increase difficulty in data analysis and application [52,53]. Medical information digitalization applications must obtain available data and set strict screening criteria to improve the repeatability and availability of data [44,45,54]. In addition, the close collaboration between patient engagement and feedback, clinical providers, and health system leaders ensures that knowledge of data generation is integrated into the analysis to obtain clinical outcomes that are meaningful. In this regard, the collection, analysis, and application of medical information digitalization need the cooperation among stakeholders from different departments and even different disciplines [47,55].

Infrastructure Resources

Most previous studies indicated that medical institutions discontinued their implementation of big data warehouses mainly due to time and costs associated with the development of a medical information digitalization system [49,56,57]. Specifically, the integration costs are normally high, and the cost of developing interfaces is even more significant. In addition, the lack of data set standardization [18,57], the sheer volume of data, and the scarcity of connectivity notably increase the difficulties involved in the implementation of medical information digitalization technology [16,47,58]. The transformation of large quantities of raw data into meaningful information also raises the issue of the allocation of capital and human resources [59]. This phenomenon leads to heavier staff workloads, especially in the absence of qualified analysts to deal with large amounts of medical data [42,60].

Regulation and Constraints

Changes in regulations and policies are another crucial real barrier that prevents the smooth implementation of a big data system [16,57]. Although these regulations and policies play an important role in the success of a medical information digitalization system, data creation and use have not been clearly and properly defined in existing regulations. In particular, the lack of understanding regarding laws and regulations, especially those related to the protection of patient's privacy, is a huge concern [54,61]. Data security and privacy is one of the most important issues in medical information digitalization [47,49,57]. Noncompliant applications of personal medical data are limited, resulting in ineffective integration and difficulties [62,63]. In addition, legal problems and disputes caused by errors in the collection and application of medical information digitalization have led to difficulty in assigning responsibility due to unclear regulations [16,64].

Operational Issue

The key to the success of technological innovation is supply, technical ability, and market demand [16,65]. Therefore, one of the major issues is how to ensure and use a large amount of confidential patient data [18,39]. In general, the organization that provides patients' medical information and data expects the information to be kept strictly confidential [15,57]. Therefore, big data from different sources should be filtered and integrated under the premise of protecting patients' profit [38,66].

Even after the collection and analysis of medical information digitalization, their application is still difficult to be commercialized due to regulatory restrictions and internal problems of medical institutions [16,54,62]. In addition, the establishment, analysis, and application of medical information digitalization without incentive system and its benefits to medical personnel may lead to less active participation [16,67].

2. Methods

Based on innovation resistance theory [68], this paper uses expertise, operation, resource, regulation, and market access barriers as the major dimensions to further investigate resistance factors encountered by medical institutions in developing medical information digitalization systems.

We first interviewed experts who all have work experience with medical digitalization, application, or management, such as physicians, medical staff, and scholars. Physicians are responsible for collecting medical data and can also use these medical data to assist in diagnosis. The digitization of medical data affects the diagnosis process. Medical staff, such as nurses, physiotherapists, and functional therapists, are responsible for assisting in collecting patient data. They can track the situation of patients after they are discharged from the hospital and extend their services to the community to the home. Scholars, such as biomedical engineering, Internet of Things, and public health, are responsible for understanding the situation of medical digitalization entering the hospital from the academic field and providing improvement strategies to assist in the implementation.

The interviews provided confidence in constructing a questionnaire distributed to key stakeholders to determine factors that inhibit them from having an effective medical data system. Responses were collected for analysis using decision-making trial and evaluation laboratory (DEMATEL) method and an importance-resistance analysis–network relation map (IRA-NRM) model to provide implicit paths for medical institutions and implement successful medical information digitalization development.

2.1. Decision-Making Trial and Evaluation Laboratory (DEMATEL) Method

This research uses DEMATEL as the main method for qualitative data analysis. This method facilitates the exploration of complex and intertwined issuable groups. In other words, this method helps determine cause and effect relationships among the criteria being assessed. References [69–72] remarked that clusters of intertwined problems can be better understood using DEMATEL, resulting in workable strategies that can be implemented by a hierarchical structure. This method is considered to be one of the best structural modeling approaches for determining contextual relationships and the weights of interdependence among system factors, as described in a causal diagram.

2.2. Importance-Resistance Analysis–Network Relation Map (IRA–NRM) Analysis

The IRA model is exclusively developed based on its original construct known as the importance-performance analysis (IPA) model [73]. Similar to IPA, the IRA model retains the same concept and structure, although the latter examines the resistance level rather than the performance of the factors [30]. Figure 1 describes the IRA model containing the four quadrants for strategic decision making through innovation resistance (IRI) and innovation importance (III) indices.

In this research, DEMATEL is used to build the NRM of each dimension and factor. The results are integrated in the IRA model to establish the IRA–NRM analysis.

The IRA model divides the factors into four categories. First, factors with high levels of importance and resistance require more resource investments for problem solving. Second, factors with a high level of importance but a low level of resistance draw greater priority in obtaining solutions because they are important and easy to address. Third, factors with low levels of importance and resistance can retain a normal status of action because they can be solved later once the important issues have been eliminated. Finally, factors with a

high level of resistance but low level of importance can be suspended because they seem to be the least meaningful and do not require timely solutions.

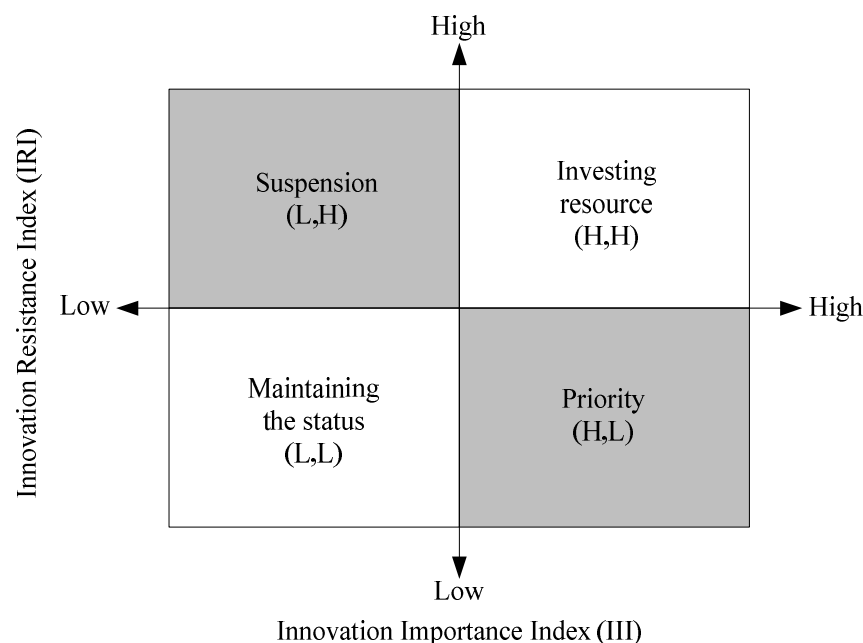


Figure 1. Innovation importance-resistance analysis (IRA) model.

Apart from the IRA model, NRM is simultaneously developed to shed light on the interdependence among factors. In other words, the map shows which factor influences the others and at what level. Strategic pathways are developed to help managers make appropriate decisions to solve resistance factors. NRM is commonly applied as the last step of DEMATEL to simplify the interdependences of factors in an easy-to-understand structure and to precisely depict such a relationship, degree of interaction, and level of influence [74].

To further determine the best strategies to remove organizational barriers to medical information digitalization system implementation, we propose an improvement model, namely, the recommended pathway analysis, which is based on the IRA–NRM analysis. After determining the critical decision problems, gaps, and dominant barriers, the factors are ranked in IRA and NRM separately. The results are integrated and analyzed to arrive at the solutions.

3. Results

3.1. Content Analysis

A semistructured interview questionnaire was designed based on literature of innovation resistance and medical information digitalization to understand resistance factors faced by medical institutions when introducing medical information digitalization systems. Thirty-two medical practitioners, including physicians, medical staff, and scholars, who are involved in data generation and have related experiences were interviewed.

Three coders conducted verbatim encoding of the interviews. During the process, differences in opinions among the coders were discussed in weekly meetings. Once the verbatim encoding was completed, the consistency of standards was examined through mutual agreement and reliability tests. The mutual agreements among coders were as follows: coders 1 and 2 = 0.87, coders 1 and 3 = 0.88, and coders 2 and 3 = 0.79. The average mutual agreement among the coders was 0.85 (Table 1), which is greater than the satisfactory result of 0.8. From the literature review and expert interviews, this research extracts 20 resistance factors and divides them into five dimensions.

Table 1. Mutual agreement between coders.

	Coder 1	Coder 2
Coder 3	0.88	0.79
Coder 2	0.87	-
Average mutual agreement: 0.85		Reliability: 0.94

3.2. DEMATEL

This research used printed questionnaires. The major respondents are physicians, medical staff, and scholars who possess knowledge of medical information digitalization. A total of 59 valid questionnaires were collected from 16 physicians (27%), 31 medical staff (53%), and 12 scholars (20%, Table 2).

Table 2. Descriptive statistics of respondents.

Background	Number of Samples	Ratio
Physicians	16	27%
Medical Staff	31	53%
Scholars	12	20%
Total	59	100%

This research conducted two procedures under IRA–NRM. The importance and difficulty of the dimensions and resistance factors as well as their distribution were determined using IRA. The interaction relationship of each dimension can be demonstrated by NRM to confirm the strategy of medical information digitalization development.

3.2.1. Main Dimensions

This research used five dimensions to conduct IRA. The distribution can be drawn from Figure 2 and Table 3. The value of d represents the degree of influence of other factors, and the importance of r represents the degree of influence of other factors. The “ $d + r$ ” shows the degree of relationship between the factors. The larger the “ $d + r$ ”, the more influential the factor is in the NRM analysis. The “ $d - r$ ” shows the strength of the influence between the factors. The smaller the “ $d - r$ ” is, the more minor affected in NRM analysis. Digitalized analysis and process (DAP) is located in the quadrant that represents high importance and low difficulty. Thus, medical institutions should improve or solve this dimension first. Regulation and constraints (RC) and infrastructure resources (IR) are located in the quadrant that represents high importance and high difficulty. Thus, medical institutions should invest resources in these dimensions. Medical data sharing (MDS) and operational issue (OI) are located in the quadrant that represents low importance and low difficulty. Thus, medical institutions should maintain the current strategy in these dimensions.

We know, through NRM, that regulation and constraints (RC) is the main dominant dimension. Therefore, medical institutions should invest in resources in the regulation and constraints (RC) to improve the strategy of digitalized analysis and process (DAP) first. Although operational issue (OI) is the dimension that is dominated, it can be enhanced by improving the four other aspects.

Through the net influence matrix (Table 4), we know that regulation and constraints (RC) influence the four other aspects. Among these relationships, the dominance on operational issue (OI) is the biggest, whereas the dominance on digitalized analysis and process (DAP) is the smallest. Digitalized analysis and process (DAP) influences infrastructure resources (IR), medical data sharing (MDS), and operational issue (OI). Among these relationships, the dominance on operational issue (OI) is the biggest, whereas the dominance on infrastructure resources (IR) is the smallest. Infrastructure resources (IR) influences medical data sharing (MDS) and operational issue (OI). Among these relationships, the dominance on operational issue (OI) is bigger than that of medical data sharing (MDS), and

the latter only influences the former. The improvement of the dimension that has higher dominance can have a better effect. Thus, we should improve regulation and constraints (RC) first and then digitalized analysis and process (DAP), infrastructure resources (IR), medical data sharing (MDS), and finally, operational issue (OI).

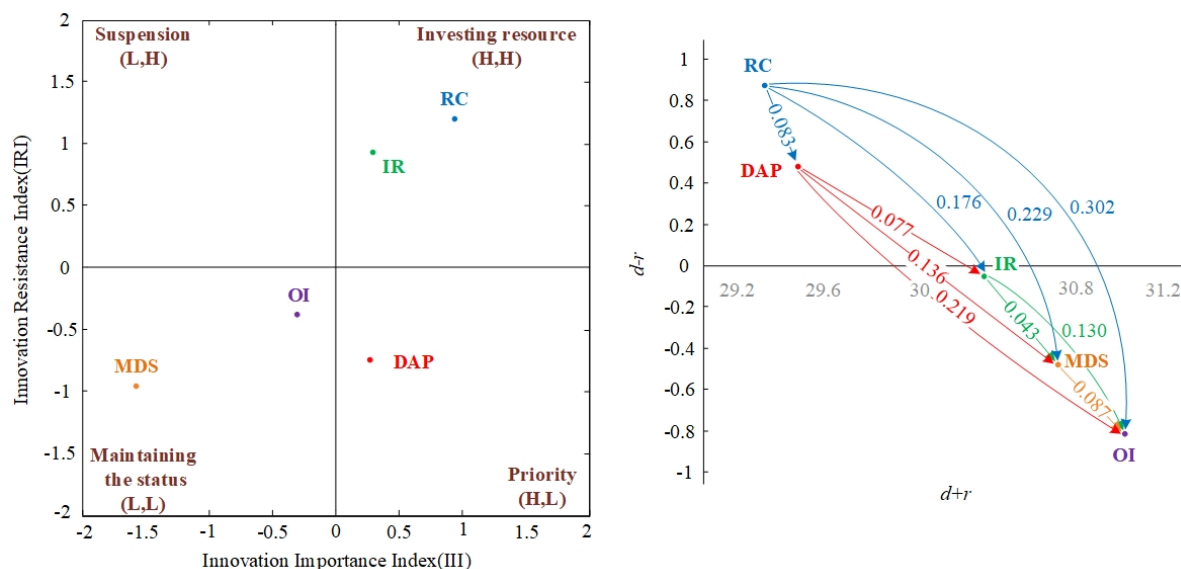


Figure 2. IRA-NRM model of the main dimensions of medical information digitalization barriers.

Table 3. Order of the main dimensions of medical information digitalization barriers and strategies.

Dimensions	IRA			NRM			Strategy
	III	IRI	(III, IRI)	$d + r$	$d - r$	$(d + r, d - r)$	
Digitalized analysis and process	0.312	−0.896	(H, L)	30.978	0.349	(+,+)	Priority
Medical data sharing	−1.627	−0.961	(L, L)	32.033	−0.321	(+,−)	Maintaining the status
Infrastructure resources	0.312	0.748	(H, H)	31.734	−0.080	(+,−)	Investing resources
Regulation and constraints	1.074	1.296	(H, H)	30.870	0.790	(+,+)	Investing resources
Operational issue	−0.071	−0.187	(L, L)	32.4469	−0.7373	(+,−)	Maintaining the status

Noted. III: innovation importance index, IRI: innovation resistance index, L: low, H: high.

Table 4. Net influence matrix of the main dimensions.

Net Influence Matrix	DAP	MDS	IR	RC	OI
Digitalized analysis and process	-				
Medical data sharing	−0.136	-			
Infrastructure resources	−0.077	0.043	-		
Regulation and constraints	0.083	0.229	0.176	-	
Operational issue	−0.219	−0.087	−0.130	−0.302	-

The whole problem recommended pathway has been proposed by integrating the analysis from IRA and NRM models to overcome medical data sharing. The ranking of the innovation importance index (III) is $RC > IR > DAP > OI > MDS$, and the ranking of innovation resistance index (IRI) is $MDS > DAP > OI > IR > RC$ (Table 5). The eight improvement paths ($RC \rightarrow OI$; $RC \rightarrow DAP \rightarrow OI$; $RC \rightarrow IR \rightarrow OI$; $RC \rightarrow MDS \rightarrow OI$; $RC \rightarrow DAP \rightarrow IR \rightarrow OI$; $RC \rightarrow DAP \rightarrow MDS \rightarrow OI$; $RC \rightarrow IR \rightarrow MDS \rightarrow OI$; $RC \rightarrow DAP \rightarrow IR \rightarrow MDS \rightarrow OI$) were determined by NRM analysis, and the advantage dimensions can improve the disadvantage dimensions (Table 5). To conclude, IRA–NRM technique combines the result of III and IRI improvement paths, and the recommended pathways are the six improvement paths ($RC \rightarrow DAP \rightarrow OI$; $RC \rightarrow MDS \rightarrow OI$; $RC \rightarrow DAP \rightarrow IR \rightarrow OI$; $RC \rightarrow DAP \rightarrow MDS \rightarrow OI$; $RC \rightarrow IR \rightarrow MDS \rightarrow OI$; $RC \rightarrow DAP \rightarrow IR \rightarrow MDS \rightarrow OI$, Table 5).

Table 5. Recommended pathways for solving the barriers regarding their main dimensions.

Rank	III		IRI	
	RC[1] > IR[2] > DAP[3] > OI[4] > MDS[5]		MDS[1] > DAP[2] > OI[3] > IR[4] > RC[5]	
Improvement paths	1.	RC[1]→OI[4]	1.	RC[5]→OI[3] (X)
	2.	RC[1]→DAP[3]→OI[4]	2.	RC[5]→DAP[2]→OI[3]
	3.	RC[1]→IR[2]→OI[4]	3.	RC[5]→IR[4]→OI[3] (X)
	4.	RC[1]→MDS[5]→MAB[4]	4.	RC[5]→MDS[1]→OI[3]
	5.	RC[1]→DAP[3]→IR[2]→MAB[4]	5.	RC[5]→DAP[2]→IR[4]→MAB[3]
	6.	RC[1]→DAP[3]→MDS[5]→MAB[4]	6.	RC[5]→DAP[2]→MDS[1]→MAB[3]
	7.	RC[1]→IR[2]→MDS[5]→MAB[4]	7.	RC[5]→IR[2]→MDS[4]→MAB[3]
	8.	RC[1]→DAP[3]→IR[2]→MDS[5]→MAB[4]	8.	RC[5]→DAP[2]→IR[4]→MDS[1]→MAB[3]
Recommended pathway	1.	RC→DAP→OI		
	2.	RC→MDS→OI		
	3.	RC→DAP→IR→OI		
	4.	RC→DAP→MDS→OI		
	5.	RC→IR→MDS→OI		
	6.	RC→DAP→IR→MDS→OI		

The IRA–NRM result of medical information digitalization barriers indicates that medical institutions can improve digitalized analysis and process (DAP) first, followed by infrastructure resources (IR) and regulation and constraints (RC) by investing resources, and finally medical data sharing (MDS) and operational issue (OI) by maintaining their status. However, regulation and constraints (RC) is a strong dimension, and operational issue (OI) is a weak dimension. Table 5 summarizes the improvement paths and the recommended pathways that medical institutions can follow to solve the main dimensions of barriers. The rest of the IRA–NRM model data, improvement paths, and recommended pathways that medical institutions can follow to solve the resistance factors of each dimension were shown on the following pages.

3.2.2. Digitalized Analysis and Process

The section focuses on digitalized analysis and process to conduct IRA. The distribution is shown in Figure 3 and Table 6. Cooperation of the personnel (DAP1) and interdisciplinary team communication (DAP4) is located in the quadrant that represents high importance and high difficulty. Thus, medical institutions should invest in resources in these factors. Analysis ability (DAP2) and data application (DAP3) are located in the quadrant that represents low importance and low difficulty; therefore, medical institutions should maintain the current strategy for these factors.

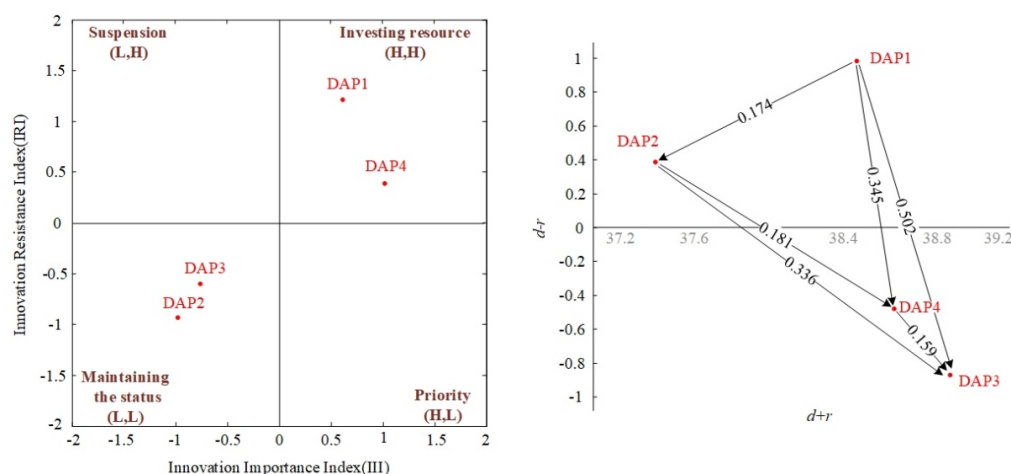
**Figure 3.** Digitalized analysis and process IRA-NRM model of medical information digitalization barriers.

Table 6. Digitalized analysis and process order of medical information digitalization barriers and strategies.

Applications	IRA			NRM			Strategy
	III	IRI	(III, IRI)	$d + r$	$d - r$	$(d + r, d - r)$	
Cooperation of the personnel	0.605	1.268	(H, H)	35.923	1.022	(+, +)	Investing resources
Analysis ability	−0.928	−0.887	(L, L)	35.034	0.343	(+, +)	Maintaining the status
Data application	−0.766	−0.707	(L, L)	36.407	−0.998	(+, −)	Maintaining the status
Interdisciplinary team communication	1.089	0.325	(H, H)	36.186	−0.367	(+, −)	Investing resources

Noted. III: innovation importance index, IRI: innovation resistance index, L: low, H: high.

The net influence matrix (Table 7) shows that cooperation of the personnel (DAP1) influences analysis ability (DAP2), interdisciplinary team communication (DAP4), and data application (DAP3). Among the relationship, the dominance on data application (DAP3) is the biggest, whereas the dominance on analysis ability (DAP2) is the smallest. Analysis ability (DAP2) influences interdisciplinary team communication (DAP4) and Data application (DAP3). Among the relationships, the dominance of data application (DAP3) is bigger than that of interdisciplinary team communication (DAP4), and the latter influences the former.

Table 7. Digitalized analysis and process net influence matrix.

Net Influence Matrix	DAP1	DAP2	DAP3	DAP4
Cooperation of the personnel	-	-	-	-
Analysis ability	−0.174	-	-	-
Data application	−0.502	−0.336	-	-
Interdisciplinary team communication	−0.345	−0.181	0.159	-

A better effect can be obtained through the improvement of the factor that has higher dominance. Thus, we should improve cooperation of the personnel (DAP1) first, followed by analysis ability (DAP2), interdisciplinary team communication (DAP4), and data application (DAP3). A recommended pathway is proposed by integrating the analysis from the IRA–NRM model to overcome digitalized analysis and process. To conclude, IRA–NRM technique combines the result of III and IRI improvement paths, and the recommended pathways are the two improvement paths (DAP1→DAP2→DAP3; DAP1→DAP2→DAP4→DAP3, Table 8).

Table 8. Recommended pathway for solving the digitalized analysis and process.

		III	IRI
Rank		DAP4[1] > DAP1[2] > DAP3[3] > DAP2[4]	DAP2[1] > DAP3[2] > DAP4[3] > DAP1[4]
Improvement paths	1.	DAP1[2]→DAP3[3]	1. DAP1[4]→DAP3[2] (X)
	2.	DAP1[2]→DAP4[1]→DAP3[3]	2. DAP1[4]→DAP4[3]→DAP3[2] (X)
	3.	DAP1[2]→DAP2[4]→DAP3[3]	3. DAP1[4]→DAP2[1]→DAP3[2]
	4.	DAP1[2]→DAP2[4]→DAP4[1]→DAP3[3]	4. DAP1[4]→DAP2[1]→DAP4[3]→DAP3[2]
Recommended pathway	1.	DAP1→DAP2→DAP3	
	2.	DAP1→DAP2→DAP4→DAP3	

3.2.3. Medical Data Sharing

This section focuses on medical data sharing to conduct IRA. The distribution can be drawn from Figure 4 and Table 9. Patient cooperation (MDS2) is located in the quadrant that represents high importance and low difficulty. Thus, medical institutions should improve this factor first. Willingness of sharing (MDS4) is located in the quadrant that represents high importance and high difficulty; therefore, medical institutions should

invest their resources in this factor. Data collection (MDS1) and information accessibility (MDS3) are located in the quadrant that represents low importance and low difficulty. Thus, medical institutions should maintain their current strategy for these factors.

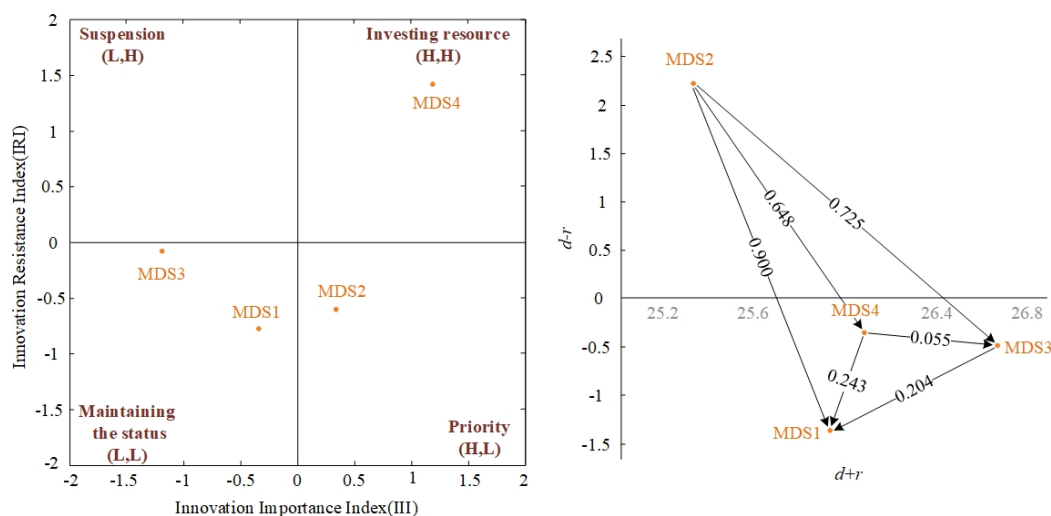


Figure 4. Medical data sharing IRA-NRM model of medical information digitalization barriers.

Table 9. Medical data sharing order of medical information digitalization barriers and strategies.

Applications	IRA			NRM			Strategy
	III	IRI	(III, IRI)	$d + r$	$d - r$	$(d + r, d - r)$	
Data collection	−0.308	−0.670	(L, L)	28.320	−1.346	(+, −)	Maintaining the status
Patient cooperation	0.286	−0.633	(H, L)	27.558	2.273	(+, +)	Priority
Information accessibility	−1.177	−0.156	(L, L)	29.033	−0.576	(+, −)	Maintaining the status
Willingness of sharing	1.199	1.458	(H, H)	28.374	−0.351	(+, −)	Investing resources

Noted. III: innovation importance index, IRI: innovation resistance index, L: low, H: high.

The net influence matrix (Table 10) reveals that patient cooperation (MDS2) influences willingness of sharing (MDS4), information accessibility (MDS3), and data collection (MDS1). Among the relationships, the dominance on data collection (MDS1) is the biggest, whereas the dominance on willingness of sharing (MDS4) is the smallest; the latter influences information accessibility (MDS3) and data collection (MDS1). In the relationship, the dominance on the data collection (MDS1) is bigger than the information accessibility (MDS3); the latter only influences the former.

Table 10. Medical data sharing net influence matrix.

Net Influence Matrix	MDS1	MDS2	MDS3	MDS4
Data collection	−			
Patient cooperation	0.900	−		
Information accessibility	0.204	−0.725	−	
Sharing will	0.243	−0.648	0.055	−

The improvement of the factor that has higher dominance can have a beneficial effect. Therefore, we should improve patient cooperation (MDS2) first, followed by sharing willingness (MDS4), information accessibility (MDS3), and data collection (MDS1). A recommended pathway is proposed by integrating the analysis from IRA and NRM model to overcome data collection (MDS1). To conclude, IRA–NRM technique combines the result of III and IRI improvement paths, and the recommended pathways are the three improvement

paths (MDS2→MDS4→MDS1; MDS2→MDS3→MDS1; MDS2→MDS4→MDS3→MDS1, Table 11).

Table 11. Recommended pathway for solving the medical data sharing.

Rank	III		IRI	
	MDS4[1] > MDS2[2] > MDS1[3] > MDS3[4]		MDS1[1] > MDS2[2] > MDS3[3] > MDS4[4]	
Improvement paths	1.	MDS2[2]→MDS1[3]	1.	MDS2[2]→MDS1[1] (X)
	2.	MDS2[2]→MDS4[1]→MDS1[3]	2.	MDS2[2]→MDS4[4]→MDS1[1]
	3.	MDS2[2]→MDS3[4]→MDS1[3]	3.	MDS2[2]→MDS3[3]→MDS1[1]
	4.	MDS2[2]→MDS4[1]→MDS3[4]→MDS1[3]	4.	MDS2[2]→MDS4[4]→MDS3[3]→MDS1[1]
Recommended pathway	1.	MDS2→MDS4→MDS1		
	2.	MDS2→MDS3→MDS1		
	3.	MDS2→MDS4→MDS3→MDS1		

3.2.4. Infrastructure Resources

This section focuses on infrastructure resources to conduct IRA. The distribution can be drawn from Figure 5 and Table 12. Faculty loading (IR4) and implementation costs (IR3) are located in the quadrant that represents high importance and high difficulty. Thus, medical institutions should invest their resources in this factor. Technical resources demand (IR1) and information reliability (IR2) are located in the quadrant that represents low importance and low difficulty. Therefore, medical institutions should maintain their current strategy for these factors.

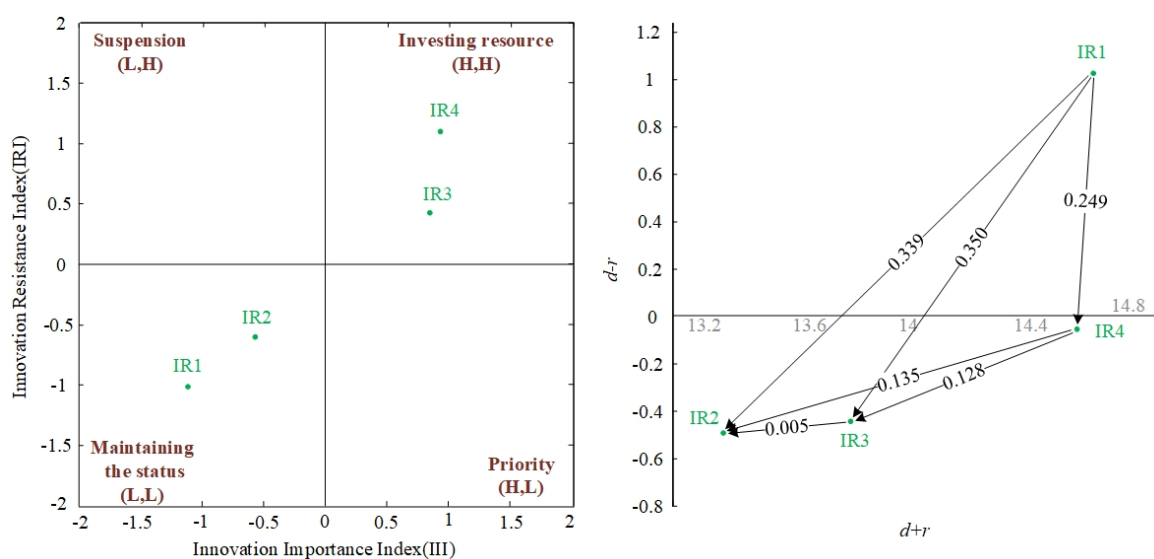


Figure 5. Infrastructure resources IRA-NRM model of medical information digitalization barriers.

Table 12. Infrastructure resources order of medical information digitalization barriers and strategies.

Applications	IRA			NRM			Strategy
	III	IRI	(III, IRI)	$d + r$	$d - r$	$(d + r, d - r)$	
Technical resources demand	−1.085	−1.038	(L, L)	14.291	0.938	(+, +)	Maintaining the status
Information reliability	−0.613	−0.552	(L, L)	12.905	−0.478	(+, −)	Maintaining the status
Implementation costs	0.802	0.376	(H, H)	13.352	−0.474	(+, −)	Investing resources
Faculty loading	0.896	1.215	(H, H)	14.205	0.014	(+, +)	Investing resources

Noted. III: innovation importance index, IRI: innovation resistance index, L: low, H: high.

The net influence matrix (Table 13) shows that technical resources demand (IR1) influence faculty loading (IR4), information reliability (IR2), and implementation costs (IR3). Among the relationships, the dominance on implementation costs (IR3) is the biggest, whereas the dominance on faculty loading (IR4) is the smallest. Faculty loading (IR4) influence information reliability (IR2) and implementation costs (IR3). Among the relationships, the dominance of faculty loading (IR4) is bigger than that of information reliability (IR2). Implementation costs (IR3) only influence information reliability (IR2).

Table 13. Infrastructure resources net influence matrix.

Net Influence Matrix	IR1	IR2	IR	IR4
Technical resources demand	-			
Information reliability	−0.339	-		
Implementation costs	−0.350	0.005	-	
Faculty loading	−0.249	0.135	0.128	-

A beneficial effect can be the improvement of the factor that has high dominance. Thus, technical resources demand (IR1) should be improved first, followed by faculty loading (IR4), implementation costs (IR3), and information reliability (IR2). A recommended pathway is proposed by integrating the analysis from IRA and NRM model to overcome Infrastructure resources. To conclude, IRA–NRM technique combines the result of III and IRI improvement paths. The recommended pathways are the three improvement paths (IR1 → IR3 → IR2; IR1 → IR4 → IR2; IR1 → IR4 → IR3 → IR2, Table 14).

Table 14. Recommended pathway for solving the infrastructure resources.

	III	IRI
Improvement paths	1. IR1[4] → IR2[3](X) 2. IR1[4] → IR3[2] → IR2[3] 3. IR1[4] → IR4[1] → IR2[3] 4. IR1[4] → IR4[1] → IR3[2] → IR2[3]	1. IR1[1] → IR2[2] 2. IR1[1] → IR3[3] → IR2[2] 3. IR1[1] → IR4[4] → IR2[2] 4. IR1[1] → IR4[4] → IR3[3] → IR2[2]
Recommended pathway	1. IR1 → IR3 → IR2 2. IR1 → IR4 → IR2 3. IR1 → IR4 → IR3 → IR2	

3.2.5. Regulation and Constraints

This section focuses on Regulation and constraints to conduct IRA. The distribution can be ascertained through Figure 6 and Table 15. Data usage (RC3) is located in the quadrant that represents high importance and low difficulty. Thus, medical institutions should improve this factor first. Regulation vagueness (RC1) and medical malpractice liability (RC4) are located in the quadrant that represents high importance and high difficulty. Therefore, medical institutions should invest their resources in this factor. Data accessibility (RC2) is located in the quadrant that represents low importance and low difficulty; therefore, medical institutions should maintain the current strategy for this factor.

The net influence matrix (Table 16) indicates that regulation vagueness (RC1) influences medical malpractice liability (RC4), data accessibility (RC2), and data usage (RC3). Among the relationships, the dominance on data usage (RC3) is the biggest, and the dominance on medical malpractice liability (RC4) is the smallest.

A beneficial effect can be achieved through the improvement of the factor that has high dominance. Thus, we should improve regulation vagueness (RC1) first, followed by medical malpractice liability (RC4), data accessibility (RC2), and data usage (RC3). A recommended pathway is proposed by integrating the analysis from IRA and NRM model to overcome regulation and responsibilities. To conclude, IRA–NRM technique combines

the result of III and IRI improvement paths, and the recommended pathways are the two improvement paths (RC1→RC2→RC3; RC1→RC4→RC2→RC3, Table 17).

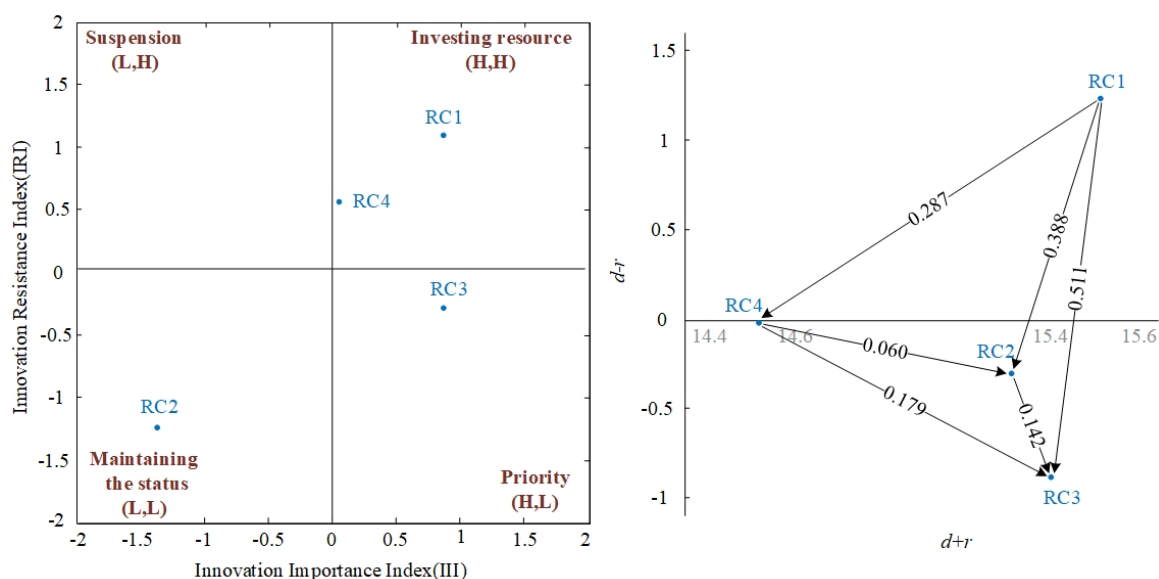


Figure 6. Regulation and constraints IRA-NRM model of medical information digitalization barriers.

Table 15. Regulation and constraints order of medical information digitalization barriers and strategies.

Applications	IRA			NRM			Strategy
	III	IRI	(III, IRI)	$d + r$	$d - r$	$(\frac{d+r}{d-r})$	
Regulation vagueness	0.705	1.012	(H, H)	15.507	1.186	(+,+)	Investing resources
Data accessibility	−1.416	−1.287	(L, L)	15.280	−0.305	(+,−)	Maintaining the status
Data usage	0.705	−0.237	(H, L)	15.383	−0.832	(+,−)	Priority
Medical malpractice liability	0.005	0.512	(H, H)	14.587	−0.049	(+,−)	Investing resources

Noted. III: innovation importance index, IRI: innovation resistance index, L: low, H: high.

Table 16. Regulation and constraints net influence matrix.

Net Influence Matrix	RC1	RC2	RC3	RC4
Regulation vagueness	-			
Data accessibility	−0.388	-		
Data usage	−0.511	−0.142	-	
Medical malpractice liability	−0.287	0.060	0.179	-

Table 17. Recommended pathway for solving the regulation and responsibilities.

		III	IRI
Rank		RC1[1] = RC3[1] > RC4[2] > RC2[3]	RC2[1] > RC3[2] > RC4[3] > RC1[4]
Improvement paths	1.	RC1[1]→RC3[1]	1. RC1[4]→RC3[2] (X)
	2.	RC1[1]→RC2[3]→RC3[1]	2. RC1[4]→RC2[1]→RC3[2]
	3.	RC1[1]→RC4[2]→RC3[1]	3. RC1[4]→RC4[3]→RC3[2] (X)
	4.	RC1[1]→RC4[2]→RC2[3]→RC3[1]	4. RC1[4]→RC4[3]→RC2[1]→RC3[2]
Recommended pathway	1.	RC1→RC2→RC3	
	2.	RC1→RC4→RC2→RC3	

3.2.6. Operational Issue

This section focuses on operational issue to conducting IRA. The distribution is presented in Figure 7 and Table 18. Patients' privacy (OI2) is located in the quadrant that represents high importance and low difficulty. Thus, medical institutions should improve this factor first. Differences between divisions (OI1) is located in the quadrant that represents high importance and high difficulty. Therefore, medical institutions should invest their resources in this factor. Lacking incentives (OI4) and worries regarding value-added service (OI3) are located in the quadrant that represents low importance and high difficulty; thus, medical institutions should suspend their current strategy for these factors.

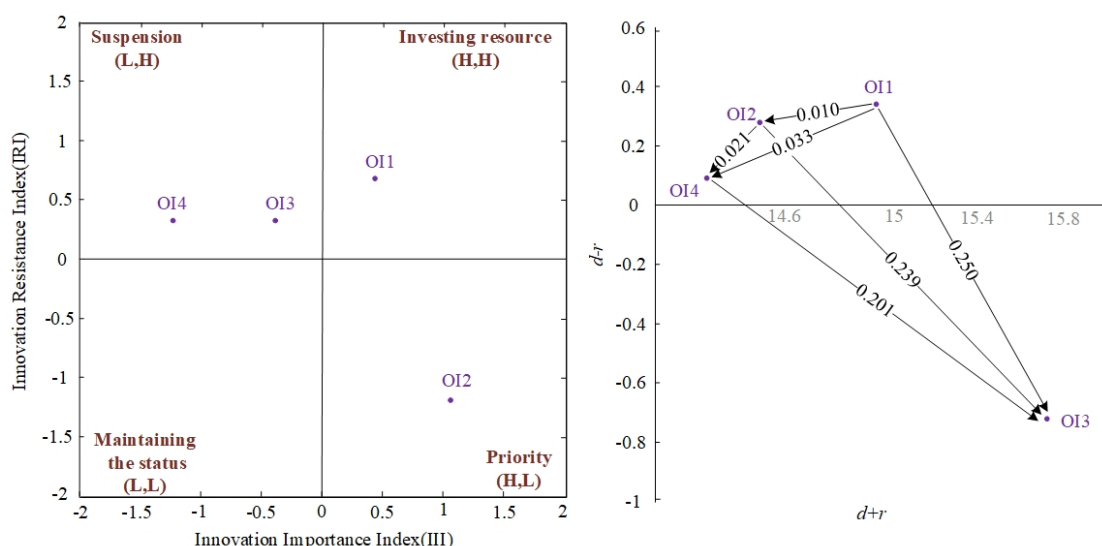


Figure 7. Operational issue IRA-NRM model of medical information digitalization barriers.

Table 18. Operational issue order of medical information digitalization barriers and strategies.

Applications	IRA			NRM			Strategy
	III	IRI	(III, IRI)	$d + r$	$d - r$	$(d + r, d - r)$	
Differences between divisions	1.160	0.789	(H, H)	14.844	0.293	(+, +)	Investing resources
Patients' privacy	0.311	−1.466	(H, L)	14.424	0.249	(+, +)	Priority
Worries regarding value-added service	−0.247	0.338	(L, H)	15.616	−0.690	(+, −)	Suspension
Lacking incentives	−1.224	0.338	(L, H)	14.313	0.148	(+, +)	Suspension

Noted. III: innovation importance index, IRI: innovation resistance index, L: low, H: high.

The net influence matrix (Table 19) reveals that differences between divisions (OI1) influences lacking incentives (OI4), patients' privacy (OI2), and worries regarding value-added service (OI3). Among the relationships, the dominance on worries regarding value-added service (OI3) is the biggest, whereas the dominance on patients' privacy (OI2) is the smallest. Patients' privacy (OI2) influences lacking incentives (OI4) and worries regarding value-added service (OI3). Among the relationships, the dominance of worries regarding value-added service (OI3) is bigger than that of lacking incentives (OI4); the dominance on worries regarding value-added service (OI3) is the smallest.

Table 19. Operational issue net influence matrix.

Net Influence Matrix	OI1	OI2	OI3	OI4
Differences between divisions	-	-	-	-
Patients' privacy	−0.010	-	-	-
Worries regarding value-added service	−0.250	−0.239	-	-
Lacking incentives	−0.033	−0.021	0.201	-

A beneficial effect can be achieved by improving the factor that has high dominance. Thus, differences between divisions (OI1) should be improved first, followed by patients' privacy (OI2), lacking incentives (OI4), and worries regarding value-added service (OI3). A recommended pathway is proposed by integrating the analysis from IRA and NRM model to overcome operational issue. To conclude, IRA–NRM technique combines the result of III and IRI improvement paths, and the recommended pathways are the three improvement paths (OI1→OI4→OI3; OI1→OI2→OI3; OI1→OI2→OI4→OI3, Table 20).

Table 20. Recommended pathway for solving the operational issue.

Rank	III		IRI	
	OI2[1] > OI1[2] > OI3[3] > OI4[4]		OI2[1] > OI3[2] = OI4[2] > OI1[3]	
Improvement paths	1.	<u>OI1[2]→OI3[4]</u>	1.	OI1[3]→OI3[2] (X)
	2.	<u>OI1[2]→OI4[4]→OI3[3]</u>	2.	OI1[3]→ <u>OI4[2]→OI3[2]</u>
	3.	<u>OI1[2]→OI2[1]→OI3[3]</u>	3.	OI1[3]→ <u>OI2[1]→OI3[2]</u>
	4.	<u>OI1[2]→OI2[1]→OI4[4]→OI3[3]</u>	4.	OI1[3]→ <u>OI2[1]→OI4[2]</u> OI3[2]
Recommended pathway	1.	OI1→OI4→OI3		
	2.	OI1→OI2→OI3		
	3.	OI1→OI2→OI4→OI3		

4. Discussion

“Medical information digitalization” is not a new terminology in the healthcare context and has been used by medical institutions in surveillance, public health, and research [18]. In addition to improving profits and reducing wasted overheads, medical information digitalization supports the process of treatment by predicting different types of diseases and improving the quality of life. Although medical information digitalization is now inclined to be internally utilized within the organizational context, in the very near future, patients could share such medical data with physicians who can employ them as part of a diagnostic toolbox when patients visit them with an ailment [5,75]. As a whole, digitalized medical information is a sizeable innovation in healthcare and in the general scenario of technology development [16,37].

Despite the undeniable benefits, medical institutions encounter several challenges; that is, the barriers significantly inhibit the development of an effective system of digitalized medical information [35]. Various factors have been discussed in several previous literatures. Bakken and Koleck mentioned the application of medical information digitalization [25], while Banerjee conducted the research of the field that the biomedical information that could be implemented into the healthcare industries. However, they did not further discuss the issues of medical information digitalization that could somehow have the interaction among each other.

This research helps to clarify the ways to improve the barriers in the development of medical information digitalization and to improve on the excellent resource allocation and strategic pathway. This research investigates barriers in effectively implementing the digitalized medical information system. [52,65]. Based on the outcomes of the IRA–NRM model, we find that regulation and responsibilities is the dominant dimension. The benefits of medical information digitalization must be based on the trust and security of providers and patients. However, the transparency and quality of data are difficult to control due to the concealment and particularity of medical processes [39,76]. Hence, the regulatory system needs to have new management thinking for the collection, access, and use of medical information to prevent asymmetry and inequality in payments and benefits [63,64]. Regulators make decisions primarily based on safety and effectiveness; therefore, these norms have economic and legal consequences, including accountability. In recent years, various countries have actively proposed appropriate assessment procedures and benchmarks to clearly define the regulatory framework of medical information digitalization [62].

Thus, in the development and future application of medical information, regulation and responsibilities are an urgent and critical problem to be solved.

Infrastructure resources (IR) and digitalized analysis and process (DAP) to the acquisition and storage of medical information digitalization are also the issues that should be further addressed; these barriers include facilities and manpower of medical information digitalization acquisition units [46,65]. Communications and information technology makes the data more accessible; therefore, medical information digitalization's real challenge involves planning, storage, unity, integration, sharing, digging, explaining, and transforming these large amounts of information [55]. The establishment of a large medical database depends on the organization, technology, professionals, and continuous feedback to ensure success [33,50,60]. In addition to ensure that the organization has adequate funding and appropriate technology to support its implementation throughout the process, the experience of those who collect data also plays an important role [16,45]. However, clinical staff must have sufficient experience and ability in the operation, presentation, device interference, specific data screening, and patient interaction in the collection of medical information digitalization, which often results in additional burden for clinical staff [42]. Therefore, effective communication across management, information technology, administration, and clinical staff can only be achieved through the organization of powerful resources and experienced personnel [45]. In the future, this research can be extended to all aspects of the development of medical information digitalization, including medical technology assessment, economic development, digital transformation, and application of artificial intelligence. This research also allows further discussion views of different stakeholders, barriers, and national regions to expand the research scope and enhance the effectiveness and contribution of the research.

5. Conclusions

This study provides two main contributions. First, based on the literature review and views of stakeholders, this article summarizes the five dimensions and twenty factors that affect the development of medical information digitalization. Second, the results of IRA-NRM emphasize the organization's investment in the development of medical information digitalization and strategies for eliminating barriers to avoid wasting resources and improve the feasibility and success rate of the application of medical information digitalization. Thus, the acquisition, management, and application of medical information digitalization are the key foundation of medical technology innovation, digital transformation, and application of artificial intelligence. This work can reduce the limitation of a narrow healthcare context and result in increasing contributions to a larger scenario. This study not only helps medical institutions and enterprises to clarify and distinguish the important issues while digitalizing medical data but also realizes the innovation and application of it. In the long term, the results provide a basis for future development direction of medical information digitalization and affect the medical industry.

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