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Addressing Barriers to Open Data Networks in Healthcare: A Systems Approach to Pandemic Response

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Original Article

Abstract

INTRODUCTION: The COVID-19 pandemic has revealed major shortcomings in healthcare data systems worldwide, particularly the need for accessible and transparent data sharing. In Iran, these shortcomings were particularly visible due to the lack of a structured open data network in the healthcare sector. Hence, this study addresses the barriers to open data networks in healthcare.

METHODS: This study used interpretive structural modeling (ISM) supported by MICMAC analysis to examine and prioritize barriers to the establishment and use of open data platforms in the Iranian healthcare system. Data were collected through expert consultations with eight experts in the field of health information and policy.

FINDINGS: The analysis revealed significant barriers to implementation, including lack of government coordination, high startup costs, and inadequate technology infrastructure. For use, the most prominent barriers included the lack of data standards, poor data management, and uncontrolled growth of unstructured data. Many of these barriers were interrelated, and some acted as root causes that hindered systemic progress.

CONCLUSION: Addressing these challenges requires coordinated strategic efforts focused on increasing ICT competencies, upgrading infrastructure, and strengthening institutional support. Establishing a functional open data network is essential to improve public health outcomes and enable faster responses to future health crises in Iran.

Keywords: Open data; Interpretive Structural Modeling; Healthcare systems; Covid-19; Coronavirus pandemic.

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Introduction

Some governments responded effectively to COVID-19, while others struggled. Past health crises, such as the Ebola outbreak, have exposed global weaknesses in data-sharing systems (1).

In the early stages of any pandemic, access to reliable epidemiological and laboratory data is essential to guide public health decisions (2). However, in many countries, including Iran, access to data was inadequate to predict the spread of the virus or assess the effectiveness of policies, and the pandemic exacerbated the case of weak healthcare systems, unclear government communications, and limited transparency about the ownership of medical data (3). At the same time, the volume and complexity of health data have increased significantly, increasing the need for structured and accessible platforms. Open data systems offer a practical solution by enabling researchers and the public to access critical datasets. For countries with aging populations, such as Iran, adopting such systems becomes essential (4) (Figure 1).

Open data refers to data sets that are freely available, reusable, and redistributable without restriction based on purpose, profession, or identity (6). These data sets should be made available in their entirety, at minimal cost, in machine-readable formats, and under conditions that allow for widespread participation and recombination with other data sources. The open data movement has gained momentum by increasing the accuracy of research, accelerating discovery, and building public trust in science (7). In public health, this enables faster responses, better policy evaluation, and better decision-making.

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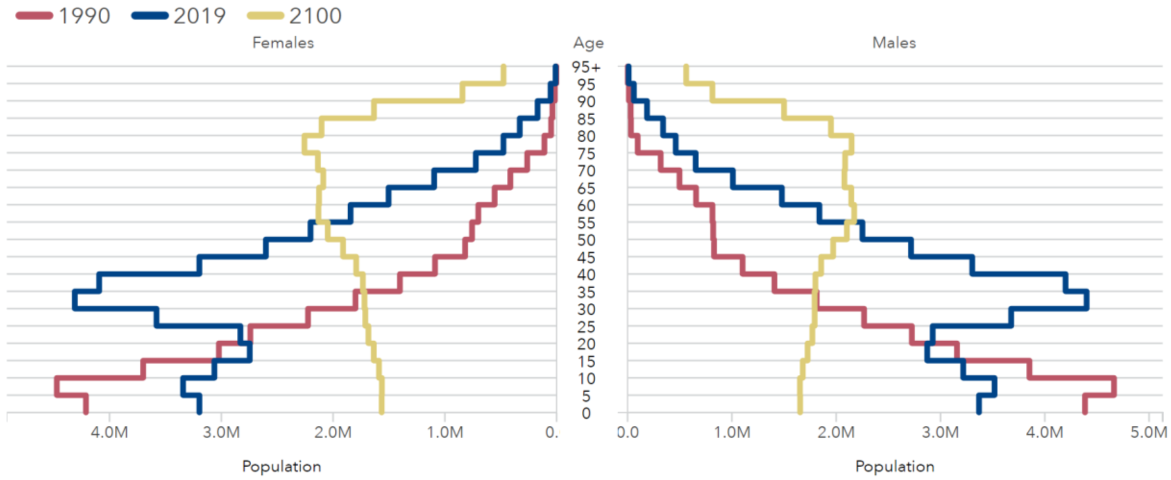

Figure 1. Distribution of age groups among men and women in 1990 & 2019 (5)

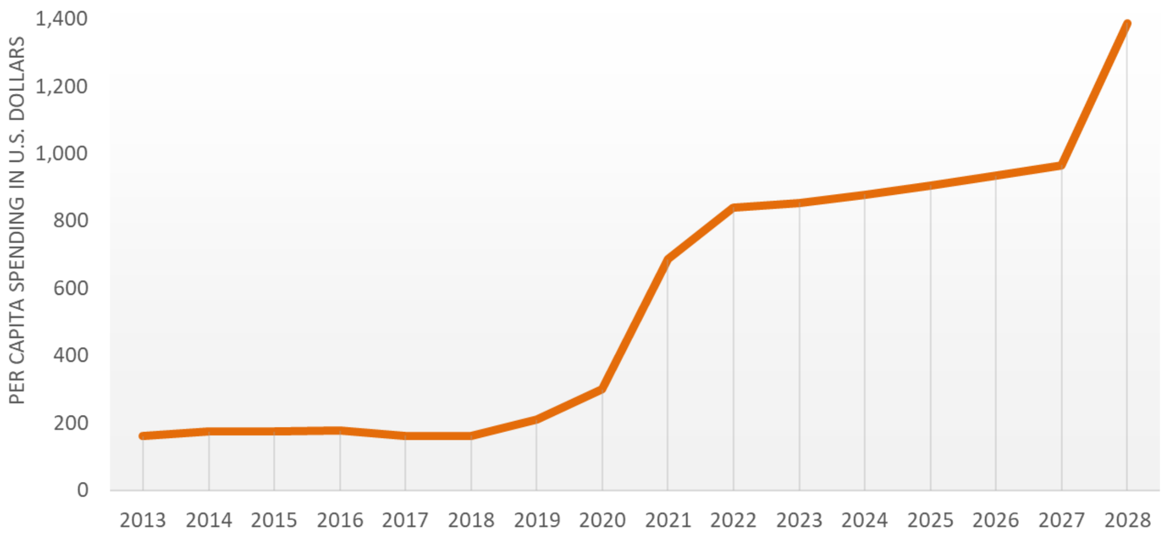

Figure 2. Forecast of the per capita consumer spending on healthcare in Iran from 2013 to 2028 in U.S. dollars (Source: World Bank)

Healthcare system in Iran, however, face challenges due to the vast amount of spending money on healthcare in the future (Figure 2). Without standards and integration tools, this data remains underused. Governments are now moving toward platforms that consolidate various types of health-related data. In Iran, rising healthcare costs and demographic shifts have made this issue more pressing. Yet, fragmented systems, lack of interoperability, and poor design have limited progress in building open data infrastructure. This study investigates the barriers to both establishing and using open data networks in Iran's healthcare system. Using a systemic approach and interpretive structural modeling, the research identifies how these barriers interact and influence one another. The goal is to support future efforts by offering a structured understanding of which obstacles must be prioritized and how they can be addressed to improve healthcare transparency, efficiency, and resilience.

Open data

Open data in healthcare has the potential to revolutionize the healthcare industry by providing access to vast amounts of data that can be used for research, analysis, and decision-making. In this literature review, we will explore recent research findings related to open data in healthcare and its impact on various aspects of healthcare services and management.

The COVID-19 pandemic has had a significant impact on the utilization of healthcare services. Moynihan, et al. (2) conducted a systematic review and found that the pandemic led to a decrease in healthcare service utilization. This finding underscores the importance of open data initiatives to track and analyze the impact of global health crises on healthcare services. Such data can help in understanding the patterns of service use and in developing strategies to mitigate the adverse effects of pandemics on healthcare access and delivery. Yaqoob, et al. (8) discussed the opportunities, challenges, and future recommendations for using blockchain in healthcare data management. Blockchain technology promises enhanced data security and interoperability in healthcare, yet it also presents significant challenges in terms of implementation and scalability. There is a critical need for further research on how open data can be integrated with blockchain technology to overcome these challenges and to create a more secure and efficient healthcare data management system. Antunes, et al. (9) proposed an architecture for federated learning in healthcare through a systematic review. Federated learning, which allows for collaborative model training across multiple institutions without sharing raw data, addresses privacy concerns associated with data sharing. This approach highlights the potential of open data to facilitate collaborative research while maintaining patient privacy, suggesting that federated learning could be a key method for utilizing open data in healthcare. Al-Metwali, et al. (1) used the health belief model to explore the acceptance of COVID-19 vaccines among healthcare workers and the general population.

Krishnamoorthi, et al. (10) developed a novel diabetes healthcare disease prediction framework using machine learning techniques. This study illustrates the significant potential of open data in developing predictive models for disease management and early intervention. By leveraging open data, healthcare providers can create more accurate and effective predictive tools to manage chronic diseases such as diabetes. Tayefi, et al. (11) highlighted the challenges and opportunities beyond structured data in the analysis of electronic health records. They emphasize that open data initiatives can address these challenges by providing access to diverse and unstructured healthcare data for advanced analytics and research. This approach can enhance the ability to perform comprehensive analyses and derive more meaningful insights from electronic health records. Tagde, et al. (12) discussed the integration of blockchain and artificial intelligence technology in e-health. Open data can facilitate the interoperability of healthcare data across different platforms and systems, enabling the seamless integration of blockchain and AI technologies for improved healthcare services. This integration could lead to more robust and secure healthcare systems, capable of providing higher quality care. Rayens and Norris (13) investigated the prevalence and healthcare burden of fungal infections in the United States. Their study demonstrates the critical role of open data in tracking and monitoring infectious diseases. Effective public health responses depend on timely and accurate data, and open data can provide the necessary information to track disease patterns and inform intervention strategies.

Recently, Yehudi, et al. (14) tried to identify five key challenges in pathogen-related data sharing, emphasizing geopolitical suppression and access difficulties. Santos, et al. (15) analyzed the U.S. response to COVID-19 testing, demonstrating how scale-up efforts saved millions of lives but also highlighting logistical hurdles. Copeland, et al. (16) explored barriers to early childhood education enrollment, including outdated technology, bureaucratic inefficiencies, and socio-economic disparities, co-developing policy solutions with stakeholders. Guan, et al. (17) applied mixed methods and community-based participatory research to assess neighborhood-level needs during the pandemic, underscoring the importance of engaging marginalized communities in health research. Finally, Mian and Glutting (18) examined workforce pipeline leaks in mental health careers, revealing financial barriers and the critical role of vocational identity in students' career decisions.

Conceptualization of open data policy

It is necessary to clarify the concept of open government data before understanding the open data policy. The concept of open government is a new and progressive approach to the way government communicates through communication technologies and innovative methods. This approach enables governments to seek help from citizens whenever needed ; For example, in solving perpetual problems, which will be the result of effective institutions and a stronger democracy (19). Open government data is a subset of public sector information made available to the public as open data (20). Such as information on accidents, diseases, detailed information about the business environment, weather and pollution, education statistics, and performance of organizations. In other words, open government data are machine-readable structured data that governments and publicly funded research organizations actively publish on the web for free access and reuse (21).

As part of its open data policy, the government must ensure that the public has access to data and information while respecting confidentiality, and that people as well as experts can participate in the policy development process. Several stages of the policy cycle are involved in open data policy, including problem definition, policy formulation, decision-making, policy implementation, and policy evaluation. All of these steps ensure that citizens have access to government data so that people can participate in the policy-making process (22). It is the right of the people to have access to a great deal of information; this awareness will enable broad decisions to be made by the people and the government (23). Policy-making and realization of open governance data paradigm, in addition to developing and increasing the scientific and technological potential of the country, has a wide effect on increasing active, comprehensive and effective participation of people and elites, and promoting capital and social trust in governance (22). Because government information is a combination of public data and personal information, based on the legal limitations of the devices, it must be determined whether the items covered by the copyright law and any other non-disclosed data are available or any license needed to access (20).

Based on Ubaldi (24) research, some of the most important values that open government data creates are: promoting accountability, transparency, accountability, and democratic control of the government (24). It can also be noted that the most important benefits of open data are: ease of providing government services, creating economic opportunities, improving public security, encouraging innovation, and reducing poverty (20). To more accurately determine the research gap, it is necessary to evaluate the research related to this concept by focusing on the exact location of the theoretical gap (open data policy, open data policy framework, open data for science and technology), the related-concept research was evaluated.

Given the prevalence of Covid-19, the global epidemic, there are crucial concerns about preventing such problems as soon as possible in the global health community. In order to address this issue, there must be a further increase in transparency in health, which can be achieved by using open data systems. The present study attempts to fill an important gap in the research background regarding measuring barriers to the operation and use of these systems. With proper access and analysis of medical data, a revolution in the country's healthcare system may be possible. In the healthcare system, the primary objective is to prevent the progression or emergence of disease and to promote the health of the community through the use of systems such as open data networks. This study is a first step towards setting up and using an open data network in the Iranian healthcare system. It is undeniable that data are one of the most important resources and assets of health care institutions, and their effective management and access to them is a major challenge (25).

A lack of access to information is one of the most common problems facing healthcare organizations in developing countries (26). Access to open data can help the organization make strategic decisions. The effectiveness of doing so leads to huge tangible benefits and eliminates unnecessary costs (27). In addition to providing many benefits to the healthcare system, setting up and utilizing a data warehouse system has many advantages. Moreover, using the systems to prevent the progression or emergence of disease in public health is the primary goal of the healthcare system today (28). This can be achieved by setting up and utilizing an open data network in Iran's health as a decision-making tool.

The present study seeks to answer what are the barriers to establishing an open data platform and using this project in Iran’s health field? and in what order can these barriers be leveled?

Methods

This study aims to identify and prioritize the barriers to establishing and using open data platforms in Iran's healthcare system through a structured, step-by-step methodology.

As illustrated in Figure 3, the research process began with a comprehensive literature review and in-depth expert interviews, which together generated an initial list of potential barriers. These barriers were compiled from both theoretical foundations and practical insights.

The next step involved classifying the identified barriers into two main categories: 1) barriers to the establishment of open data platforms (BEOD), and

2) barriers to their use (BEUD). With input from eight experts in the field of health information and systems, a refined selection of the most critical factors in each group was validated for further analysis (43).

Following this, the study applied Interpretive Structural Modeling (ISM) to uncover the hierarchical relationships between the selected barriers in each group. The ISM process involved creating a Structural Self-Interaction Matrix (SSIM), developing the reachability matrix, and determining the levels of each variable through iterative partitioning. This modeling helped to reveal which barriers were root causes and which were influenced by others. Subsequently, MICMAC analysis (Matrix of Cross-Impact Multiplications Applied to Classification) was conducted to classify the barriers based on their driving power and dependence. This step identified the most influential and most reactive barriers in the system and grouped them into four clusters: autonomous, dependent, linkage, and independent. The final stage of the methodology focused on managerial interpretation, where the structured findings from ISM and MICMAC were synthesized to extract actionable insights. This step translated the systemic relationships into practical recommendations, highlighting strategic intervention points for policymakers and healthcare managers aiming to implement open data platforms effectively.

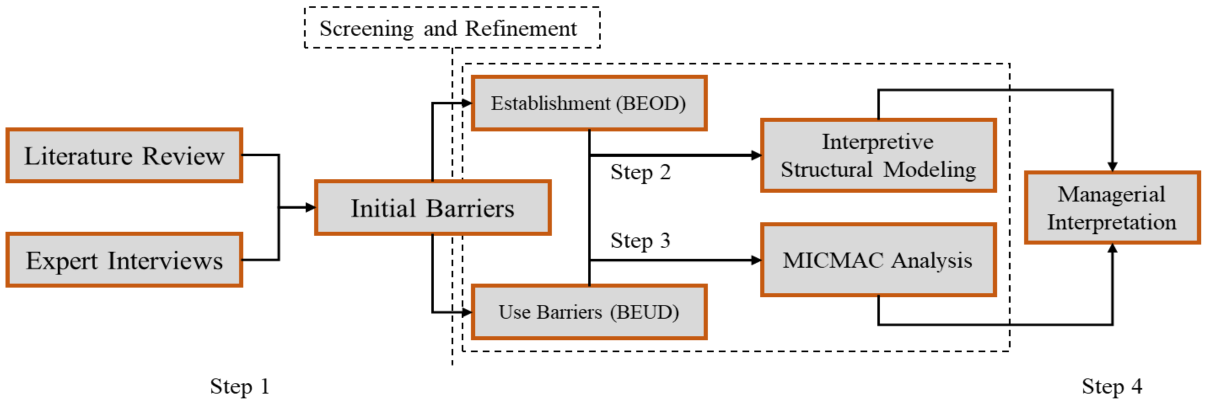

Figure 3: The research process

Table 1: Barriers of Implementation and Use of an open data system extracted from literature and preliminary interviews before reviewing by experts

	Factor	Reference
Barriers of Implementation	Government disagreement	(29)
	Expensive system implementation	(30)
	Lack of financial credit for the establishment of an open data system	(30)
	Support of the Ministry of Health	(31)
	Possibility of poor system design	(32)
	Technology infrastructure - data language - bandwidth (availability of sufficient bandwidth for a wide range of data)	(33)
	Data content and formatting and programming language for displaying data	(34)
	Computer skills / software of personnel	(30)
	The severe shortage of human resources in the Ministry of Health of Iran	(28)
	Lack of access to the open data network in all parts of the country (for example, where access to a network or connection is restricted for political or other reasons.	(3 &43)
	Inadequate equipment (including the number of computers and clinical terminals of the patient)	(30 &35)
	Information storage (cloud space)	(34)
	The resistance of medical centers and hospitals in the direction of open data platforms (due to transparency of performance)	Experts
	Fear of medical centers for further tensions and problems with insurance (a series of information is available to insurance companies that leads to abuse and neglect of insurance)	Experts
Barriers of Use	Continuous production of data mass	(36)
	Lack of necessary standards for data production and dissemination	(6 &33)
	Unreliability of published data	(33)
	Lack of data management	(4, 31, 33)
	Error in entering information (nurses' carelessness)	(34)
	Violation of patient privacy	(37)
	Requires significant computations to analyze big data	(38)
	Data usage -data analysis training	(39&40)
	Financial, legal, regulatory, or policy requirements that require the use of data	(22& 41)
	Lack of access to technical support services to address the problem in the system	(33)
	Strong security factor in preventing the system from being hacked	(33& 42)

Table 2. Hierarchical level assignment of BEOD network in Iran's healthcare system

BEOD factor	Output set	Input set	Level
Government disagreement	1	1, 2, 4, 6, 7	1
Expensive system implementation	1, 2, 3	2, 4, 6, 7	2
Possibility of poor system design	3	2, 3, 4, 6, 7	1
Lack of proper technology infrastructure, data language, and bandwidth (availability of sufficient bandwidth for a wide range of data)	1, 2, 3, 4	4	3
Insufficient computer skills/software of personnel	5	5	1
The severe shortage of human resources in the Ministry of Health of Iran	1, 2, 3. 6	6	3
Inadequate equipment (including patient counts and clinical terminals)	1, 2, 3, 7	7	3
The resistance of medical centers and hospitals in the direction of open data platforms (due to transparency of performance)	8	8	1

Findings

This section presents the key findings from the two-stage analysis of barriers related to the establishment and use of open data platforms in Iran's healthcare system. A total of 25 potential barriers were identified through a combination of literature review and preliminary expert interviews. Specifically, 14 barriers were related to the establishment of open data systems and 11 were associated with their use within the healthcare sector. These factors are outlined in Table 1. Following expert review, eight key barriers from each category were selected for further analysis and hierarchical structuring using the ISM and MICMAC methodologies.

Among the factors found in the literature, the authors discussed all the factors with an initial group of experts. The primary experts were three active professors in the field of e-health. After the factors were approved, factors 13 and 14 were added to the list by experts. A number of these factors are selected and examined in the following sections. These factors have been selected based on the opinions of the main experts and on the consensus of the group. There are eight health experts, including three primary experts. It has been found that previous research has not identified any barriers to the implementation and use of open data systems in the health sector. Based on expert input and structured modeling, the study identified how these barriers interact, influence one another, and vary in their level of impact. The first part of the analysis focuses on barriers to establishment (BEOD), while the second addresses barriers to use (BEUD). Using Interpretive Structural Modeling (ISM) and MICMAC techniques, the research not only classified these barriers hierarchically but also revealed which ones serve as root causes and which are more reactive or dependent in nature. The following subsections detail the results of each step.

BEOD analysis

The second step of the methodology involved identifying the key problem variables. Initially, 14 barriers related to the establishment of an open data platform were extracted from literature and expert interviews. After expert validation, eight critical factors were selected for further analysis and hierarchical structuring using the ISM and MICMAC techniques (Table 2). To explore the relationships among these variables, a SSIM was constructed based on the judgments of eight healthcare experts who completed structured questionnaires. Following the ISM procedure, the reachability matrix was developed, and barriers were leveled accordingly.

The hierarchical levels indicate the position of each barrier within the structural system. For example, barriers like government disagreement and poor system design are located at the lower levels of the hierarchy, suggesting they are root causes with broader systemic impact. On the other hand, barriers such as lack of infrastructure or shortage of human resources appear higher in the hierarchy and are more dependent on the resolution of other foundational problems. Using the final reachability matrix and the derived levels, a structural model was developed to visually represent the interactions among the barriers. This model, shown in Figure 4, provides a clear roadmap for decision-makers by illustrating how certain issues cascade through the system and where intervention efforts should be focused first.

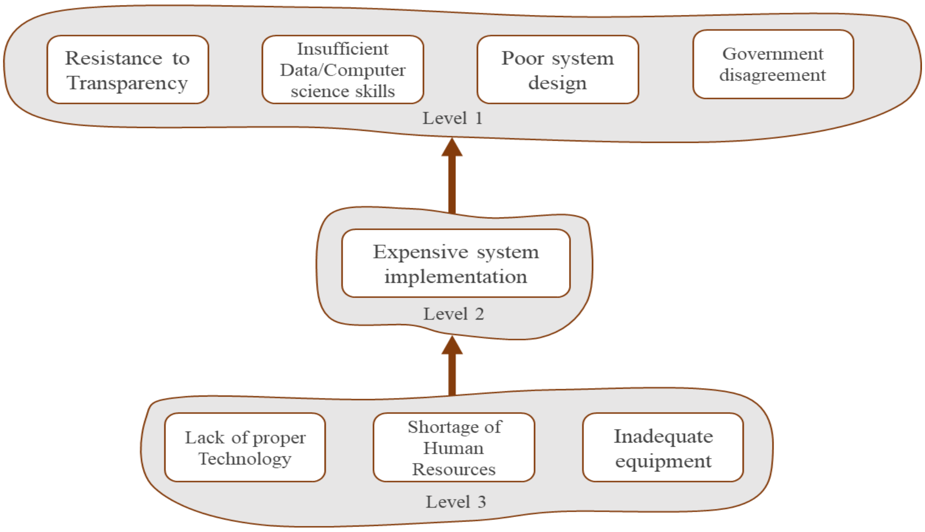

Figure 4. ISM model BEOD network in the field of health in Iran.

As shown in Figure 4, the barriers to establishing an open data platform in Iran's healthcare system were structured into three levels. Foundational challenges included inadequate equipment, a severe shortage of skilled personnel, and poor ICT infrastructure, all pointing to deep-rooted infrastructural gaps. High-level barriers, such as resistance from medical centers, limited ICT skills, poor system design, and lack of government alignment, were shaped by these underlying factors. The cost of system implementation occupied an intermediate position, acting as a bridge between foundational and systemic issues. Unlike countries such as Germany or the UK, Iran lacks national programs for developing ICT capacities, with key roles like ICT health expert largely absent.

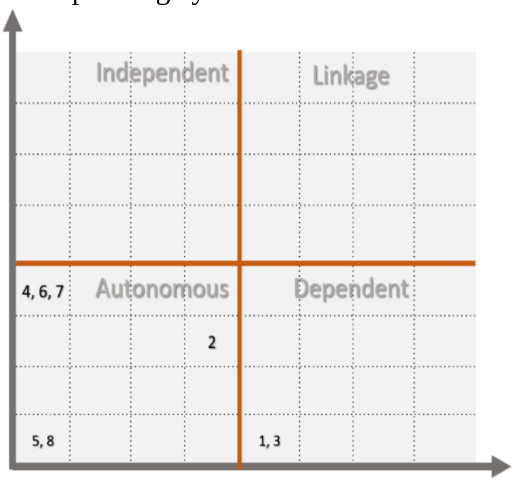

Figure 5. Clustering of barriers to establishing an open data platform in the field of health in Iran using the MICMAC method

Figure 5 illustrates the results of the MICMAC clustering, where barriers were categorized into four groups based on their influence and dependence. Notably, government disagreement and poor system design emerged as dependent elements, heavily shaped by other variables, making them critical system-level consequences. On the other hand, foundational barriers like inadequate infrastructure, manpower shortages, and insufficient equipment had the strongest driving power. While some barriers appeared more autonomous or isolated in impact, these three remained central to the platform's failure, indicating the need for priority intervention.

BEUD analysis

In the third step of the study, the focus shifted from establishing open data platforms to the challenges related to their usage within the healthcare system. Initially, 14 potential barriers were identified through literature review and expert insights. After validation by a panel of eight domain experts, eight critical barriers were selected for deeper structural analysis using the ISM and MICMAC methodologies (Table 3). Similar to the Step 2, a SSIM was constructed based on expert input to assess the contextual relationships among the selected factors. Experts completed structured questionnaires to indicate the directional influence between each pair of variables. These judgments were then used to build the binary reachability matrix, from which level partitioning was performed. The resulting levels reveal how some barriers serve as root causes while others are largely dependent on upstream issues. For example, lack of necessary standards for data production and dissemination is identified as a key driver affecting multiple downstream challenges. In contrast, violation of patient privacy and unreliability of published data are highly dependent and are shaped by the influence of other variables.

Table 3. Hierarchical level assignment of BEUD in Iran's healthcare system

BEUD factors	Output set	Input set	Level
Continuous production of data mass	1, 3, 4, 6, 7, 8	1, 2, 4	3
Lack of necessary standards for data production and dissemination	1, 2, 3, 4, 5, 6, 7, 8	2	4
Unreliability of published data	3	1, 2, 3, 4, 5, 8	1
Lack of data management	1, 3, 4, 6, 7, 8	1, 2, 4	3
Error in entering information (nurses' carelessness)	3, 5	2, 5	2
Violation of patient privacy	6	1, 2, 4, 6, 8	1
Requires significant computations to analyze big data	7	1, 2, 4, 7	1
Strong security factor in preventing the system from being hacked	3, 6, 8	1, 2, 4, 8	2

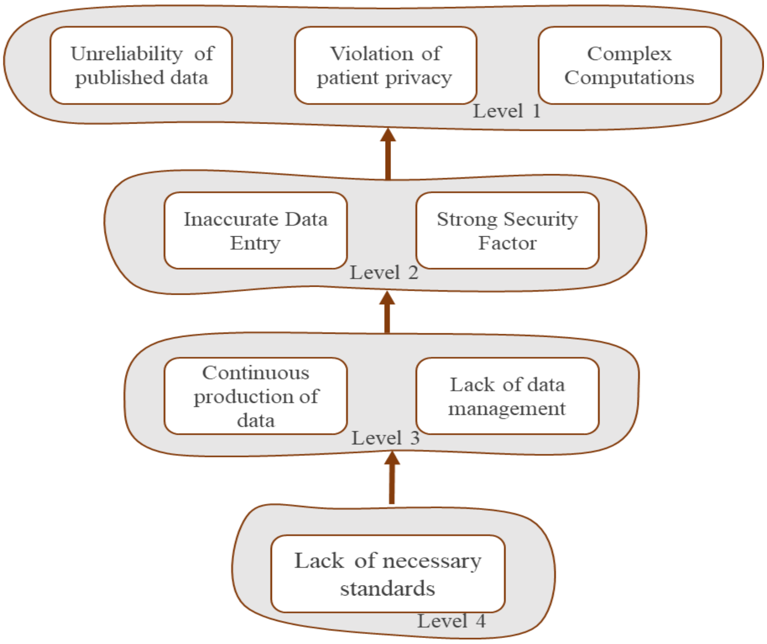

Figure 6. ISM model BEUD network in the field of health in Iran

Based on these levels, a structural model was developed to illustrate the hierarchy and influence pathways among the BEUD barriers. As shown in Figure 6, this model helps identify which challenges require immediate managerial and technical intervention to facilitate the effective use of open data systems in healthcare.

According to Figure 6, the barriers to using the open data network project in the healthcare system in Iran were at four levels. At the most basic level, the root cause is the lack of standards required for the production and dissemination of data. Also, continuous production of data mass and lack of data management were at the third level. Error in entering information (nurses' carelessness), strong security factor in preventing the system from being hacked was secondary. Also, the barrier of unreliable published data, violation of patient privacy, the need for significant calculations to analyze big data was placed at the highest level, which indicates that it is affected by other barriers and should be concerned seriously.

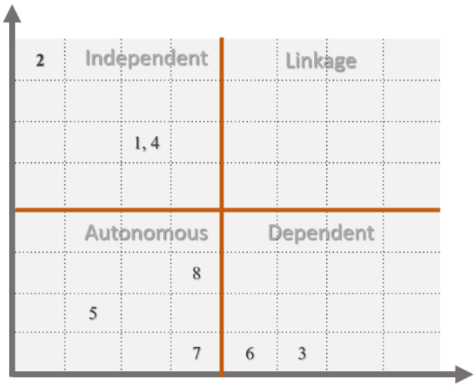

Figure 7. Clustering of BEUD project in the field of health in Iran using MICMAC method

According to Figure 7, barriers such as unreliability of published data and violation of patient privacy are highly dependent and shaped by other factors, making them critical yet reactive obstacles to open data adoption. Unlike countries like Germany, where legal protections and anonymization tools are well-established, Iran lacks comparable safeguards, intensifying privacy concerns. Foundational issues like continuous data production, lack of standards, and poor data management have had a major influence on the failure to adopt open data systems, with the absence of standards emerging as the most impactful. Other barriers, though still relevant, exert less influence and occupy a more independent role in the system's overall inefficiency.

Discussion and Conclusion

This section (Step 4) provides an in-depth discussion of the findings and offers managerial insights derived from the ISM and MICMAC results. The study reveals that the lack of an operational open data network in Iran's healthcare system is not the result of a single failure but rather the outcome of several layered and interconnected structural issues. By analyzing these barriers systematically, this section highlights the most critical leverage points for action and suggests strategic interventions that can be undertaken by decision-makers in both government and healthcare institutions. Using ISM, the research identified key barriers that are rooted in both technical limitations and institutional resistance. At the foundational level, challenges such as inadequate ICT infrastructure, limited bandwidth, lack of computer skills among personnel, and a severe shortage of human resources within the Ministry of Health are among the most influential barriers. These variables exert significant downstream influence, shaping the feasibility and design of any potential open data initiative. Without resolving these basic capacity gaps, open data networks are unlikely to be successfully launched or sustained. The MICMAC analysis reinforced this structural complexity by demonstrating how certain barriers, while visible and urgent, are actually dependent on deeper systemic factors. For instance, high-level issues like government disagreement and resistance from hospitals are not root causes. They are influenced by underlying weaknesses in infrastructure, training, and policy coordination. This finding has important implications for managers and policymakers. Efforts to address resistance or to enforce adoption through policy mandates will likely fail if these deeper problems remain unaddressed. Instead, a sequenced, systems-based strategy is needed, where technical readiness and workforce development are prioritized before pushing for institutional compliance.

Furthermore, in the analysis of barriers to the use of open data (as opposed to its establishment), the study found that the lack of necessary standards for data production and dissemination plays a foundational role. This issue, together with poor data management and the continuous production of unstructured data, forms a bottleneck that prevents any meaningful utilization of shared information. Despite the existence of data in various formats and systems, their inconsistency and inaccessibility undermine any effort toward evidence-based policymaking or clinical decision support. These results indicate that even if an open data platform is technically implemented, its value will be limited unless these standards and data governance mechanisms are clearly defined and enforced. Another important insight is the degree to which cultural and institutional attitudes influence the trajectory of digital transformation in healthcare. The study highlighted barriers such as the fear of insurance-related consequences, reluctance from medical centers to expose performance data, and a general lack of trust in system security. These are not technical issues. They reflect managerial culture, legal ambiguity, and absence of strategic communication. Health managers and national planners must recognize that open data adoption is as much a behavioral shift as it is a technological reform. Therefore, soft interventions such as awareness campaigns, transparent data-use policies, and pilot projects in select hospitals may help reduce this resistance over time.

Finally, this study provides a conceptual structure that can guide future implementation efforts. By prioritizing root-level barriers and carefully managing interdependencies among variables, managers can avoid ad-hoc approaches that waste time and resources. The ISM model can serve as a diagnostic tool for policymakers to identify leverage points, while the MICMAC matrix offers a roadmap for sequencing reforms. Building an open data ecosystem in healthcare is a complex task that requires coordination across government ministries, legal frameworks, IT departments, and frontline medical professionals.

The path forward should be gradual, coordinated, and grounded in the systemic relationships revealed through this analysis.

While this study provides a structural understanding of the barriers to establishing and using open data platforms in Iran's healthcare system through the ISM method, several avenues remain for further investigation. The ISM approach, though insightful in mapping interrelationships, does not assign weights to barriers. To address this, future research can integrate ISM with methods such as the Analytical Network Process (ANP) to prioritize the barriers once their relationships are mapped. Additionally, Structural Equation Modeling (SEM) can be employed to statistically validate and quantify the strength of these relationships, offering deeper empirical insights. Researchers are also encouraged to explore the potential of blockchain-centered open data networks, especially in healthcare, to address concerns around transparency, privacy, and data integrity. Given the rising importance of home healthcare services, future studies should also focus on open data frameworks tailored to at-home care delivery, which remains underexplored in Iran.

Beyond healthcare, the concept of open data can be extended to Iran's energy sector, which faces mounting sustainability and efficiency challenges. A preliminary assessment of energy-related open data initiatives can be conducted using Data Envelopment Analysis (DEA) to evaluate the efficiency of different project portfolios based on input-output performance (45). This would allow for strategic project selection and investment prioritization (46). Furthermore, transparency in healthcare could be enhanced by analyzing treatment pricing data across providers, followed by simulation-based modeling to assess which pricing strategies might yield the most benefit for policy reform (47). Collectively, these suggestions provide a roadmap for expanding open data research and application across multiple sectors critical to Iran's development.

Compliance with Ethical Guidelines

All ethical considerations have been observed in this research.

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Author's Contributions

All authors contributed equally in this research.

Conflict of Interests

The authors declare no conflict of interest.

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