Research on Influencing Factors of Healthcare Big Data Assetization from a Data Lifecycle Perspective: An Empirical Analysis Based on the Fuzzy-DEMATEL-ISM Method

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Abstract

Purpose/Significance: Currently, the assetization of medical and health data is progressing slowly both domestically and internationally, which seriously affects the implementation of national medical and health big data strategies and industrial development. Identifying the key influencing factors of medical and health big data assetization and proposing targeted countermeasures is of great significance for tapping the potential value of medical and health big data.

Methods/Process: This paper first identifies the influencing factors of medical and health big data assetization based on a combination of literature analysis and expert interviews, then identifies factor ranking and inter-factor relationships using the Fuzzy-DEMATEL-ISM method, and finally proposes promotion strategies for medical and health big data assetization based on the analysis results of the influencing factors.

Results/Conclusion: The study finds that medical and health big data assetization is influenced by 23 factors across six dimensions: data collection, data storage, data processing, data management, data application, and related environment. Among them, four factors such as data sharing and data trading are the most direct influencing factors of medical and health big data assetization; eleven factors including standard management and privacy protection are key factors connecting the bottom and top layers; and eight factors such as technical support and data integration are root influencing factors of medical and health big data assetization. Based on the research conclusions, recommendations for promoting medical and health big data assetization are proposed, focusing on the related environment and drawing from five dimensions of the medical and health big data lifecycle.

Full Text

Research on the Influencing Factors of Medical and Health Big Data Assetization from the Perspective of Data Life Cycle: An Empirical Analysis Based on the Fuzzy-DEMATEL-ISM Method

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Abstract

[**Purpose/Significance**] The current slow progress of medical and health data assetization both domestically and internationally has seriously hindered the implementation of national medical and health big data strategies and industrial development. Identifying the key influencing factors of medical and health big data assetization and proposing targeted countermeasures is of great significance for tapping the potential value of medical and health big data. [**Method/Process**] This study first identifies the influencing factors of medical and health big data assetization through a combination of literature analysis and expert interviews. It then employs the Fuzzy-DEMATEL-ISM method to identify factor rankings and inter-factor relationships. Finally, based on the analysis results, promotion strategies for medical and health big data assetization are proposed. [**Result/Conclusion**] The findings reveal that medical and health big data assetization is influenced by 23 factors across six dimensions: data acquisition, data storage, data processing, data management, data application, and related environment. Among these, four factors—including data sharing and data trading—are the most direct influencing factors of medical and health big data assetization. Eleven factors, such as standard management and privacy protection, serve as key connectors between bottom and top layers. Eight factors, including technical support and data integration, constitute the root influencing factors. Based on these conclusions, recommendations are proposed to promote medical and health big data assetization across five dimensions of the medical and health big data life cycle, centered on the related environment.

Keywords: Medical and Health Big Data; Data Assetization; Data Life Cycle; Fuzzy-DEMATEL-ISM Method
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1 Introduction

Medical and health big data refers to health-related information generated during disease prevention, treatment, and health management processes [1]. In addition to the 5V characteristics of big data [2], medical and health big data possesses complex attributes including ambiguous ownership legal attributes, high-value economic attributes, social linkage social attributes, and high-sensitivity humanistic attributes. As a crucial national strategic resource [3], analyzing and mining the value of medical and health big data can improve healthcare service efficiency, optimize medical resource allocation, and enhance productivity in the medical industry. Data assetization represents a key bottleneck for unlocking the value of medical and health big data and is essential for addressing issues such as data asset rights confirmation, value assessment, and reuse. Medical and health big data assetization enables effective development and utilization of big data, generating supportive effects for society, medical institutions, and pharmaceutical and big data-related industries. Given the enormous volume of medical data, achieving data assetization and tapping potential data value is an urgent problem requiring solution.

The term "data asset" was first proposed by Peters in 1974, evolving from concepts of information resources and data resources [4]. Currently, there is no consensus on the definition of data assets. This study adopts the concept from the *Data Asset Management Practice White Paper (Version 5.0)*: "Data assets refer to data resources recorded in physical or electronic form that are legally owned or controlled by enterprises, can be measured or traded, and can directly or indirectly bring future economic benefits to enterprises." "Data assetization" is the process of transforming data into usable assets [5]. Current domestic and international research on data assetization focuses on theoretical aspects, including concept definition [6][7][8], data asset value realization [9][10], and data trading [11]. Zhang et al. [8] studied fundamental theoretical issues of government data asset attributes, ownership principles, and pricing methods through status analysis and theoretical discussion. Chen et al. [10] proposed five dimensions for measuring power data asset value, including granularity, activity, multidimensionality, application value, and risk value, using the entropy weight method and TOPSIS approach to calculate data asset value. Due to issues such as easy replication and potential misuse of sensitive power data, Wang et al. [11] designed a blockchain-based power data assetization and trading system. However, existing literature lacks research on influencing factors of data assetization, with few studies focusing on medical and health big data assetization, resulting in relatively slow development of medical and health big data assetization management.

Regarding the path to data assetization, some scholars have examined the data assetization process. Li et al. [12], using power grid data assetization as an example, proposed that the process can be divided into four stages: standardization, privacy rating, processing, and product packaging. Ji et al. [13] divided the data assetization process into three major stages: establishing industry consensus, data processing, and data package encapsulation. Some scholars have also discussed specific aspects of the data assetization process. For instance, Hariri et al. [14] analyzed data mining processes by comparing traditional data technologies with artificial intelligence technologies. You et al. [15] proposed a framework for data asset quality assessment, providing a reference model for evaluating data asset quality. Although existing research has discussed the data assetization process or its components, different scholars have varying understandings of the process, and no clear, standardized assetization process model has been formed, particularly lacking theoretical guidance and implementation pathways specific to medical and health big data assetization.

Literature review reveals two gaps in current research on influencing factors of medical and health big data assetization: First, in terms of research objects, existing studies focus primarily on government data and power data assetization, with insufficient attention to medical and health big data assetization. Compared with government and power data, medical and health big data has unique characteristics, such as involving highly sensitive personal privacy information [16] and including multiple forms such as pure data, images, and audio. Therefore, existing research frameworks and conclusions cannot be directly applied to medical and health big data assetization. Second, regarding influencing factors of data assetization, there is no standardized theoretical framework for medical and health big data assetization processes, and few studies have examined influencing factors of the data assetization process. Since data assetization is a critical prerequisite for realizing data value, and mature theoretical guidance, technical tools, and implementation routes are currently lacking, researching key influencing factors of the data assetization process and proposing corresponding promotion strategies is of significant importance.

In summary, this study focuses on the issue of influencing factors of medical and health big data assetization. Through literature analysis and expert interviews, it constructs an influencing factor system for medical and health big data assetization. It then combines the fuzzy decision-making trial and evaluation laboratory (DEMATEL) method with interpretive structure modeling (ISM) to identify key influencing factors and hierarchical structures among factors. Finally, based on the analysis results, it proposes countermeasures and suggestions for realizing medical data value, providing practical references for promoting medical and health big data assetization.

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2 Construction of the Influencing Factor Model for Medical and Health Big Data Assetization

This study employs literature analysis, grounded in the medical and health big data life cycle and its internal and external environment, to identify dimensions of influencing factors for medical and health big data assetization: data acquisition, data storage, data processing, data management, data application, and related environment. Preliminary specific influencing factors are identified, and through expert interviews, comprehensive expert opinions are synthesized to finalize the influencing factors of medical and health big data assetization, facilitating subsequent identification of key factors and analysis of inter-factor relationships.

2.1 Medical and Health Big Data Life Cycle

Data life cycle theory developed from information life cycle theory. Current research by domestic and international scholars primarily focuses on its connotation, indicating that the data life cycle represents a complete data framework from generation to consumption stages [17]. The data life cycle theory has been applied across various domains. Xiao et al. [18] standardized privacy security across stages including collection, storage, access, application, sharing, and destruction for biomedical big data life cycles. Wu et al. [19] constructed a medical and health data life cycle model for wearable devices by analyzing each stage of the wearable device medical and health data life cycle, incorporating acquisition, transmission, integration, interaction, and feedback. Current medical data-centered life cycle models are limited, mostly examining specific parts or sources of medical data, while life cycle research predominantly focuses on scientific research data, government data, and other data types [20]-[22]. Michener et al. [20] proposed a scientific data life cycle model as a circular structure where each cycle includes management planning, data collection, data validation, data description, data preservation, discovery, integration, and analysis. Attard et al. [21] presented an open government data life cycle cycle model covering four central stages: data modeling, publication, discovery, and integration. Cao et al. [22] created a seven-stage data life cycle model from the perspective of research activity data output and application, encompassing "data management plan—data collection—data analysis—data publication—data preservation—data sharing—data reuse." Literature review indicates that most stages are similar across different domain data life cycles.

Given limited research on medical and health big data life cycles, this study combines stage divisions from other domain data life cycles with the medical data value chain [23] to divide the medical and health big data life cycle into data acquisition, data storage, data processing, data management, and data application, with new data generated during the data application stage entering the next cycle. Across all stages of the medical and health big data life cycle, the internal and external environment provides venues and space for data exchange.

2.2 Influencing Factors of Medical and Health Big Data Assetization

Based on the above analysis of the medical and health big data life cycle, this study finalizes the dimensions of influencing factors for medical and health big data assetization, including data acquisition, data storage, data processing, data management, data application, and related environment. The study primarily employs a combination of literature analysis and expert interviews to identify influencing factors of medical and health big data assetization.

First, in the preliminary identification of influencing factors, existing medical data life cycles and other domain data life cycles are considered. CNKI is selected as the literature retrieval database. Advanced search is conducted in CNKI with "data life cycle" as the keyword, limiting journal sources to CSSCI and Peking University Core categories, with a time span from 2018 to 2022. After removing conference notices and less relevant entries, 50 valid records are obtained. NVIVO software is then used for statistical analysis to preliminarily identify influencing factors for each stage of the medical and health big data life cycle, with representative literature sources marked, as shown in Table 1 .

Table 1 Medical and Health Big Data Assetization Influencing Factors Based on Text Analysis

Dimension	Influencing Factors	Representative Literature
Data Acquisition	Data Sources; Data Standards; Platform/Tool Standards	Li Han [24]; Huang Jing et al. [25]; Zhang Fan et al. [26]
Data Storage	Data Classification and Grading; Data Security; Privacy Protection	Wang Huoming et al. [27]; Xiao Ai et al. [18]
Data Processing	Data Cleaning; Data Integration; Data Transformation; Data Analysis	Zhang Fan et al. [26]; Jiang Hong et al. [28]; Lu Li et al. [29]; Cao Xiuli et al. [22]
Data Management	Data Quality; Cost Management; Operations Management	Zhang Fan et al. [26]; Wang Huoming et al. [27]; Jiang Hong et al. [28]; Huang Qianqian et al. [30]
Data Application	Data Sharing; Data Trading; Market Supply and Demand; Data Ownership Rights	Li Han [24]; Zhang Fan et al. [26]; Xiao Ai et al. [18]; Huang Qianqian et al. [30]
Related Environment	Institutional Guarantee; Supporting Tools; Technical Support; Talent Team	Li Han [24]; Xiao Ai et al. [18]; Wu Wenchen et al. [31]

Subsequently, to enhance the reliability of the listed influencing factors, expert interviews are conducted to evaluate the impact degree of each factor on medical and health big data assetization. Considering the current status of medical and health big data assetization in China, the influencing factors listed in Table 1 are explained according to the characteristics of medical and health big data and compiled into a questionnaire. Through email and online meetings, 13 experts with years of work or research experience in the medical and health field are interviewed, including 6 hospital information management personnel and 7 medical and health big data technology experts. Expert opinions are used to delete, supplement, and clarify each factor' s concept. The following principles are followed when organizing influencing factors: Principle of comprehensiveness, where identified factors should be as comprehensive as possible without obvious overlap; Principle of representativeness, where final factors should have certain representativeness; Principle of majority rule, where factor selection requires agreement from more than half of the experts.

After two rounds of expert interviews, expert opinions on factor definitions, classifications, and revisions converge. Based on the research results, an expert opinion table is compiled as shown in Table 2 , and 23 influencing factors of medical and health big data assetization are finalized, as presented in Table 3 .

Table 2 Expert Interview Opinions

Expert Opinion	Modification
Merge "Data Standards" and "Platform/Tool Standards" into "Standard Management"	Both belong to standard management and need consideration throughout the entire data assetization process, should be classified under data management
Adjust "Data Quality"	Add "Data Acquisition Methods"
Add "Data Acquisition Methods"	Collecting missing or inconsistent data increases storage costs. Data quality affects data value. Data acquisition is the starting point of all data applications. If not done properly, subsequent remediation requires significant cost.
Add "Data Visualization"	Intuitive display of data processing results makes it easier to discover patterns in large datasets.
Add "Science Popularization"	Through science popularization, more people can understand the connotation, value, processing flow, and legal regulations of medical and health big data.

Table 3 Influencing Factors of Medical and Health Big Data Assetization

Code	Dimension	Factor	Definition
A1	Data Acquisition	B1 Data Sources	Sources of medical and health big data, including patient medical visits, medical equipment, biochemical analysis, bioinformatics, pharmaceutical enterprises, research platforms, wearable devices, medical platforms, medical apps, etc.
		B2 Data Acquisition Methods	Including sensor collection, manual entry, import, interfaces, etc.
		B3 Data Quality	Integrity, timeliness, accuracy, consistency, and promptness of medical and health big data.
		B4 Data Classification and Grading	Classifying and grading medical and health big data by content, source, function, and data type, and constructing reasonable and complete data indexes.
A2	Data Storage	B5 Data Security	Protecting medical and health big data security through encryption, disaster recovery and backup, firewalls, anti-tampering, electronic signatures, identity authentication, and access control.

Code	Dimension	Factor	Definition
		B6 Privacy Protection	Protecting user privacy information such as names, ID numbers, and phone numbers in accordance with the Personal Information Protection Law.
A3	Data Processing	B7 Data Cleaning	Reviewing and validating data, including checking consistency, handling invalid and missing values, data reduction, and integration.
		B8 Data Integration	Logically or physically integrating multi-source or heterogeneous data into a unified dataset while ensuring data security and integrity.
		B9 Data Transformation	Transforming medical and health big data from one representation form to another through normalization, discretization, and conceptual hierarchy generation.
		B10 Data Analysis	Mining and extracting useful information and knowledge hidden in medical and health big data to discover correlations and patterns.
		B11 Data Visualization	The ability to display data and transmit information through data visualization.

Code	Dimension	Factor	Definition
A4	Data Management	B12 Cost Management	Operation costs (storage, integration, maintenance), management costs (labor, indirect costs), construction costs (planning, collection, verification), and resource costs (hardware infrastructure).
		B13 Operations Management	Using regulations, target management, ISO9000 quality management systems for data management activities, setting various data access permissions, and continuously tracking and analyzing medical and health big data circulation.
		B14 Standard Management	Standards for metadata, reference data, master data, data transmission, and storage; specifications for platform and tool standards regarding equipment compatibility and database functions/performance.
A5	Data Application	B15 Data Sharing	Centralizing raw or processed data for internal use by medical and health institutions in clinical trials, drug analysis, medical performance evaluation, risk prediction, etc.

Code	Dimension	Factor	Definition
		B16 Data Trading	Value exchange behavior of medical and health big data as products or services between medical and health institutions and other entities to meet different needs.
		B17 Market Supply and Demand	Quantity of medical and health big data resources suppliers can provide; quantity demanders are willing and able to purchase.
		B18 Data Ownership Rights and Interests	Issues regarding who owns medical and health big data and profit distribution during data trading.
A6	Related Environment	B19 Institutional Guarantee	Formulation of relevant laws, regulations, and policies during data assetization to prevent market manipulation, fraud, and other illegal activities.
		B20 Software and Hardware Facilities	Typical tools in medical and health big data assetization, including hardware for data collection and management; databases and data warehouses for storage; data analysis platforms and text/image analysis tools for processing; data middle platforms and business intelligence for decision-making applications.

Code	Dimension	Factor	Definition
		B21 Technical Support	Technologies used in medical and health big data assetization, including data transmission, encryption, authentication, desensitization, and computational analysis.
		B22 Talent Team	Talent reserves and professionalism in medical and health big data-related fields.
		B23 Science Popularization	Education and promotion of medical and health big data connotation, value, processing flow, application fields, legal regulations, intellectual property rights, and technical methods.

3.1 Theoretical Definitions

The DEMATEL method is a systems analysis approach for studying causal relationships among elements within complex decision-making systems. It leverages expert experience and knowledge to evaluate interrelationships among factors in complex structural systems, identifying and analyzing key influencing factors through transformation and calculation of influence matrices [32]. The ISM model is a primarily qualitative method in modern systems engineering that decomposes complex systems into several simple subsystems with hierarchical relationships, thereby simplifying complex systems [33][34].

Traditional DEMATEL requires experts to express influence degrees among factors using precise values based on experience and knowledge, but experts exhibit excessive individual differences and subjective thinking [35]. Therefore, this study introduces fuzzy set theory into the DEMATEL method to mitigate the impact of scoring precision and subjectivity on factor relationship evaluation. Since DEMATEL can only determine the importance of a factor within the influencing factor system but cannot clarify the internal structure and logic among factors [35], while ISM excels at expressing structural relationships among factors but inadequately explains the degree of influence [36], this study combines DEMATEL with ISM to form the Fuzzy-DEMATEL-ISM method.

3.2 Fuzzy-DEMATEL-ISM Integrated Modeling Steps

This study first constructs a medical and health big data assetization influencing factor system through literature analysis and the Delphi method. It then uses the Fuzzy-DEMATEL method to identify key influencing factors of medical and health big data assetization. Finally, it builds an ISM model to conduct systematic and hierarchical research on the influencing factors, clarifying their mechanisms of action. The research framework and specific implementation steps are shown in Figure 1 [Figure 1: see original paper].

Figure 1 Research Framework and Specific Implementation Steps

4.1 Influencing Factor Analysis Based on Fuzzy-DEMATEL-ISM

To further identify interrelationships among influencing factors of medical and health big data assetization and their structural relationships, six medical and health big data experts are invited to score the mutual influence degrees among factors based on optimal group decision-making size. Scoring results are compiled and converted into triangular fuzzy numbers. Using the CFCS method for defuzzification, the direct influence matrix is obtained. MATLAB 2018b software is then used for data processing to derive the comprehensive influence matrix T, shown in Table 4 .

Table 4 Comprehensive Influence Matrix T

Based on the comprehensive influence matrix T, the influence degree, influenced degree, centrality, and cause degree of each factor are calculated according to Step 6, as shown in Table 5 . The causal relationship diagram of medical and health big data assetization influencing factors is then plotted, as shown in Figure 2 [Figure 2: see original paper].

Table 5 Comprehensive Influence Matrix Analysis

Using MATLAB software, the average value =0.23 and standard deviation σ=0.05 of all elements in comprehensive influence matrix T are calculated, determining the threshold $\lambda = +\sigma = 0.28$. The comprehensive influence matrix T plus the identity matrix is transformed into the overall influence matrix H. According to Step 9, the reachability matrix K is obtained, as shown in Table 6 .

Table 6 Reachability Matrix K

Based on the reachability matrix K and following Steps 10 and 11, the reachable set, antecedent set, and common set are calculated to construct the hierarchical table of medical and health big data assetization influencing factors, as shown in Table 7 . The ISM model of medical and health big data assetization influencing factors is then plotted, as shown in Figure 3 [Figure 3: see original paper].

Table 7 Hierarchical Division

Figure 3 Multi-level Hierarchical Structure Model of Medical and Health Big Data Assetization Influencing Factors

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4.2.1 Analysis of Key Factors

(1) Centrality Analysis
Centrality reflects the importance of each influencing factor within the medical and health big data assetization influencing factor system. In terms of centrality, Standard Management (B14), Cost Management (B12), Data Sharing (B15), Operations Management (B13), and Data Trading (B16) are the top five among the 23 influencing factors, belonging to Data Management (A4) and Data Application (A5) dimensions. This indicates that in the process of medical and health big data assetization, management and inter-organizational data sharing and trading most significantly affect assetization efforts. The influence degrees of Standard Management, Cost Management, and Operations Management rank second, third, and fifth respectively, suggesting these three factors significantly impact other factors. Their influenced degrees rank sixth, seventh, and ninth. The multi-level hierarchical structure model shows that the three data management factors are closely related to other influencing factors. Combined with the ISM model diagram, Data Trading and Data Sharing are located in the first two layers, representing the most fundamental factors affecting medical and health big data assetization. Their influenced degrees also rank first and second, indicating these two factors are most susceptible to other factors' influence, thus representing key nodes among influencing factors.

(2) Cause Degree Analysis
Based on positive and negative cause degree values, medical and health big data assetization influencing factors can be divided into cause factors and effect factors. Research findings show that cause factors with larger cause degrees, in descending order, are: Technical Support (B21), Talent Team (B22), Data Sources (B1), Institutional Guarantee (B19), Software and Hardware Facilities (B20), Data Cleaning (B7), Science Popularization (B23), Data Integration (B8), Standard Management (B14), Data Classification and Grading (B4), Data Analysis (B10), and Data Transformation (B9). These factors possess strong proactivity; enhancing their effects will promote improvements in other effect factors, thereby enhancing the entire system application. All factors in

the Related Environment dimension (A6)—Institutional Guarantee, Software and Hardware Facilities, Technical Support, Talent Team, and Science Popularization—are cause factors, indicating that the institutional, facility, technical, talent, and promotional environment significantly influences the occurrence of medical and health big data assetization. As the main subject of assetization, Data Sources undoubtedly constitute a cause factor. Data Cleaning, Data Integration, Data Analysis, and Data Transformation belong to the Data Processing dimension (A3). Data processing is a critical step for data application and value addition and represents a key influencing factor of medical and health big data assetization. Standard Management serves as a normative constraint ensuring the standardization of medical and health big data sharing and trading, representing an important foundation for data application and development. Data standard management helps break data silos and release data value. Data Classification and Grading is a prerequisite for ensuring data security and an important component of data assetization.

Effect factors are easily constrained by other factors. Among the 11 effect factors, Data Trading (B16), Data Sharing (B15), and Market Supply and Demand (B17) rank first, second, and fourth in effect degree, with their influenced degrees also ranking in the top three, indicating that as the three most intuitive dimensions of medical and health big data assetization, they possess strong passivity. Privacy Protection (B6) and Data Security (B5) rank third and fifth in effect degree, and third and eighth in influenced degree, demonstrating that as medical data involving public information and health conditions with high sensitivity, privacy and security issues are susceptible to other factors' influence. The leading effect factors primarily belong to the Data Application (A5) and Data Storage (A2) dimensions, which can be indirectly promoted through improvements in other factors.

4.2.2 Multi-level Hierarchical Structure Model Analysis

(1) Bottom-layer Influencing Factors

Bottom-layer factors are fundamental, including Levels L5, L6, and L7 in the ISM model. Bottom-layer factors include: Data Classification and Grading (B4), Data Cleaning (B7), Data Integration (B8), Institutional Guarantee (B19), Software and Hardware Facilities (B20), Talent Team (B22), Technical Support (B21), and Science Popularization (B23). These factors are related to the environment, data processing, and data storage during medical and health big data assetization. Related environment factors (A6)—Institutional Guarantee, Software and Hardware Facilities, Technical Support, Talent Team, and Science Popularization—are basic guarantees for medical and health big data assetization, affecting data sharing and trading, data value realization, and the assetization process. Data Cleaning and Data Integration are factors in the Data Processing dimension (A3), extracting data meeting specific needs and values from multi-source and heterogeneous data to ensure accuracy and usability for data sharing and trading. Data Classification and Grading belongs to the Data Storage dimension (A2), representing an important foundation for data security protection and a major challenge for medical and health big data assetization. Bottom-layer influencing factors affect top-layer factors through some middle-layer factors, often exerting subtle influences on medical and health big data assetization.

(2) Middle-layer Influencing Factors

Middle-layer factors include Levels L3 and L4 in the ISM model, serving as hubs that connect to the medical and health big data assetization process through their impact on top layers. Middle-layer factors include: Data Acquisition Methods (B2), Data Quality (B3), Data Security (B5), Privacy Protection (B6), Data Transformation (B9), Data Analysis (B10), Data Visualization (B11), Data Ownership Rights and Interests (B18), Cost Management (B12), Operations Management (B13), and Standard Management (B14). These indirect factors involve complex components across all stages of the medical and health big data life cycle. Cost Management, Operations Management, and Standard Management belong to the Data Management dimension (A4). Data management aims to improve data quality, ensure data security, and advance data resource integration and trading processes, also serving as key connectors between bottom-layer and other middle-layer factors. Data Acquisition Methods and Data Quality belong to the Data Acquisition dimension (A1), where different acquisition methods affect data quality, and ensuring data quality is essential for realizing data value. Data Security and Privacy Protection are factors under the Data Storage dimension (A2). Due to the 特殊性 of the medical industry and the sensitivity of medical and health data, privacy protection must be strengthened during assetization. Data Transformation, Data Analysis, and Data Visualization belong to the Data Processing dimension (A3), as medical and health data must undergo varying degrees of processing before sharing and trading. Data Ownership Rights and Interests is a factor under the Data Application dimension (A5), representing an important prerequisite for secure and orderly data flow and assetization, affecting data development, utilization, and market trading. Middle-layer factors indirectly affect medical and health big data assetization by influencing top-layer factors through bottom-layer factor participation.

(3) Top-layer Influencing Factors

Top-layer factors include Levels L1 and L2 in the ISM model, representing direct drivers of medical and health big data assetization and the most immediate considerations for promoting the assetization process. Top-layer factors include: Data Trading (B16), Data Sources (B1), Data Sharing (B15), and Market Supply and Demand (B17). Data Sharing, Data Trading, and Market Supply and Demand belong to the Data Application dimension (A5), demonstrating that data application plays an important role in advancing medical and health big data assetization and realizing data value creation. Market Supply and Demand is the fundamental driving force for medical and health big data assetization, stimulating data sharing and trading behaviors, while data sharing and trading represent manifestations of data value realization that can drive data industry development. Data Sources belongs to the Data Acquisition dimension (A1). As a direct influencing factor of medical and health big data assetization, insufficient authority and reliability of data sources directly affect data value realization. The key to improving top-layer factor performance lies in addressing dilemmas in bottom-layer and middle-layer factors.

5.1 Conclusions

This study addresses the theme of influencing factors of medical and health big data assetization. Based on existing literature and expert interviews, combined with data life cycle theory, it extracts 6 dimensions and 23 influencing factors. Six medical big data experts are invited to evaluate the influencing factors, and the Fuzzy-DEMATEL-ISM method is used to analyze the evaluation results, identify key influencing factors, and analyze their internal relationships, yielding the following conclusions.

First, bottom-layer influencing factors include the related environment and data processing and storage dimensions. Factors in the related environment (Institutional Guarantee, Software and Hardware Facilities, Technical Support, Talent Team, Science Popularization) and data processing (Data Cleaning, Data Integration) dimensions are cause factors with high cause degrees, representing the most fundamental factors affecting medical and health big data assetization that continuously and long-term influence other factors in the entire system. Data Classification and Grading under the data storage dimension shows high influence and centrality, representing an important foundation for ensuring data security. Continuous improvement of these factors will affect middle-layer factors and ultimately promote medical and health big data assetization by influencing top-layer factors.

Second, middle-layer influencing factors are relatively complex, involving five dimensions of the medical and health big data life cycle. Factors in the data management dimension (Cost Management, Operations Management, Standard Management) show large influence and centrality in the system and serve as key connectors between bottom-layer and middle-layer factors in the ISM model, exerting profound influence on promoting medical and health big data assetization and requiring focused attention. Factors in data acquisition (Data Acquisition Methods, Data Quality), data storage (Data Security, Privacy Protection), and data application (Data Ownership Rights and Interests) dimensions are mostly highly influenced, belonging to effect factors that directly affect top-layer factors and thus influence the assetization process. The data processing dimension (Data Transformation, Data Analysis, Data Visualization) prepares for data application and belongs to cause factors that affect top-layer factors through bottom-layer and some middle-layer factors.

Third, top-layer influencing factors include data application and data acquisition dimensions. Factors in the data application dimension (Data Sharing, Data

Trading, Market Supply and Demand) have the most direct impact on medical and health big data assetization. Effective measures targeting some factors in this dimension can directly and rapidly improve obstacles in the assetization process. The Data Sources factor under the data acquisition dimension is a very important cause factor for medical and health big data assetization, directly affecting the assetization process.

5.2 Recommendations

Since the related environment provides exchange venues and space for the entire data life cycle, this section discusses development recommendations for improving medical and health big data assetization from five dimensions of the medical and health big data life cycle, centered on the related environment and based on the above analysis.

(1) Data Acquisition: Ensuring Data Quality
As the fundamental step of data assetization, data acquisition affects top-layer factors or directly influences the medical and health big data assetization process by collecting authoritative and reliable data. Different sources of medical and health big data affect acquisition methods. Currently, medical and health big data primarily originates from major medical institutions, mainly including data generated from patient medical behaviors, clinical data, and experimental data, which ensures data authenticity and reliability. Additionally, with information technology development, wearable devices supported by IoT, monitoring equipment for temperature and pressure, etc., can collect vast amounts of real-time medical and health data with great variety. Network data collected in real-time and comprehensively by smart terminals supported by mobile communication technology also constitutes a major component of medical and health big data. Data acquisition methods affect data quality. Therefore, during medical and health big data acquisition, data from medical institutions should be primary, supplemented by monitoring equipment data and network data to ensure data quality.

(2) Data Storage: Protecting Data Privacy and Security
Data storage indirectly affects medical and health big data assetization by influencing middle-layer factors through bottom-layer factors such as related systems and technologies. Due to the high sensitivity of medical and health data, medical and health big data must be classified and graded, with data security authorization mechanisms established for privacy and confidential data to facilitate implementation of relevant laws and regulations such as the Data Security Law and Personal Information Protection Law, reducing privacy leakage risks. Second, facing increasingly complex data environments, technologies such as data encryption, disaster recovery and backup, and identity authentication are needed to ensure medical and health big data storage security. Meanwhile, relevant medical institutions should establish sound industry self-discipline mecha-

nisms, with relevant personnel signing medical and health big data confidentiality agreements. Governments should formulate industry standards and increase penalties for medical and health big data privacy breaches.

(3) Data Processing: Mining Hidden Information in Data
The data processing stage most requires bottom-layer factor support such as technology and skilled personnel to indirectly affect medical and health big data assetization through middle-layer and top-layer factors. The main task of the data processing stage is to extract value from massive, complex data. This process employs big data processing technologies such as data desensitization, data mining, data fusion, data visualization, and predictive analytics, requiring numerous skilled professionals. Moreover, medical and health big data assetization involves multiple disciplines including medicine, management, law, and finance, requiring composite talents who understand medical data, big data technology, data security, and legal regulations. Therefore, scientific training mechanisms must be established to strengthen the cultivation of technical and composite talents. Additionally, emphasis should be placed on imparting cutting-edge theoretical knowledge and technologies such as IoT, cloud computing, and artificial intelligence, while focusing on practical ability and innovation capacity development.

(4) Data Management: Improving Data Management Efficiency
Data management-related factors serve as critical middle-layer influencing factors that affect other middle-layer and top-layer factors through bottom-layer factors, advancing data assetization. In complex data environments, medical institutions must expand coverage of emerging technologies such as blockchain, cloud computing, and 5G across all stages of the data life cycle. Through technologies like data collection and analysis, distributed storage, precise identification and tracking, and data traceability, security throughout the entire medical and health big data life cycle can be ensured. Since medical and health big data and its assetization involve multiple entities and medical institutions, non-unified standards will cause data chaos, and subsequent unification of data formats and standards will consume substantial resources. Therefore, standards for data acquisition and storage must be formulated, and unified data storage platforms established to accelerate data acquisition and storage while reducing costs and promoting data valorization.

(5) Data Application: Leveraging Data Value Initiative
Data application-related factors, as the most direct influencing factors of data assetization, depend on bottom-layer and middle-layer factors to improve obstacles in medical and health big data assetization. First, constructing and improving the basic data rights system is the foundation for data trading and supply [38]. Data asset attributes and ownership rights must be clarified, and policy and legal systems for medical and health big data established to lay the foundation for assetization. Second, as a complex assetization object, medical and health big data requires government departments to standardize trading rules across regions and establish fair, just, and open trading supervision mech-

anisms, clarifying regulatory departments and measures responsible for medical and health big data supervision to protect trading entities' interests. Then, during data sharing and trading processes involving multi-party collaborative supervision, regulatory technologies such as big data, blockchain, and artificial intelligence can be used for intelligent data identification and monitoring, data traceability, etc., to ensure privacy security during sharing and trading.

Beyond the above recommendations for the medical and health big data life cycle process, medical institutions can also collaborate with online platforms and official accounts to publish popular science knowledge, promoting to the general public the value, processing flow, application fields, and legal regulations of medical and health big data. This can both alleviate public concerns about data leakage and attract relevant talent.

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Note: Figure translations are in progress. See original paper for figures.