Journal of Information Systems Engineering and Management
2024, 9(1), 24423
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Optimization Path for Management Decision-Making of Chinese Public Hospitals Under the Background of Big Data

Qinqin Wu [1], Nur Ajrun Khalid [2*]

[1] Ph.D candidate, School of Social Sciences, Universiti Sains Malaysia, Gelugor, Malaysia
[2] Doctor, School of Social Sciences, Universiti Sains Malaysia, Gelugor, Malaysia
* **Corresponding Author:** nurajrun@usm.my

Citation: Wu, Q., & Khalid, N. A. (2024). Optimization Path for Management Decision-Making of Chinese Public Hospitals Under the Background of Big Data. *Journal of Information Systems Engineering and Management*, *9*(1), 24423.
https://doi.org/10.55267/iadt.07.14509

ARTICLE INFO

Received: 24 Oct 2023
Accepted: 31 Dec 2023

ABSTRACT

This study examines how Big Data might improve Chinese public hospital management. A comprehensive study examines how data diversity, storage efficiency, analytics tools, and information system complexity affect decision-making. A carefully selected quantitative dataset from Chinese public hospitals is used in the study. Analyses use structured medical records, semi-structured billing data, and unstructured patient comments. The sample size of 115 was chosen for statistical robustness and multiple regression analysis best practices, which recommend 10-20 observations per predictor variable for estimate. Multiple linear regression analysis highlights amazing correlations and stresses data diversity, storage efficiency, analytics tools, and information system sophistication in decision efficiency. The study helps healthcare executives and regulators understand the complex relationship between regression coefficients and modified R-squared value. Also evaluated are Chinese public hospitals' strengths and weaknesses. Strengths include data integration, analytics, and advanced information systems. The report emphasizes data quality and cultural transformation, which impact Big Data and decision-making. The report emphasizes data consumption and advanced analytics to empower healthcare decision-makers. This research informs Chinese public hospital strategic reforms to improve resource allocation, patient care, and efficiency. This paper demonstrates how Big Data can impact healthcare decision-making. It enriches academic discourse and guides healthcare stakeholders through modern management with relevant insights and practical advice.

Keywords: Healthcare Management, Big Data Integration, Decision Efficiency, Analytics Tools, Data Quality, Big Data.

INTRODUCTION

Big Data alters healthcare management, enabling innovation and optimization. This study analyzes how Big Data integration affects Chinese public hospital decisions. Big Data processes massive amounts of data from many sources to affect healthcare administrators' and legislators' decisions. Healthcare management and resource allocation alter with Big Data (Song et al., 2018). Growing patient numbers and changing healthcare needs require resource optimization, cost-efficiency, and quality improvement in Chinese public hospitals (Benzidia, Makaoui, & Bentahar, 2021).

Data-driven insights and technology have transformed healthcare worldwide and in China. Big Data improves healthcare outcomes, resource allocation, and operational efficiency in Chinese public hospitals (Lavalle et al., 2020). However, fulfilling these transformative promises is difficult. Big Data integration into hospital management requires data quality assurance, information system design, and data-driven culture (Benzidia et al., 2021). Complex healthcare Big Data regulatory compliance and ethical issues exacerbate the issue. Compliance with Chinese healthcare Big Data ethics requires monitoring and modification (Ma, Meng, & Du, 2023).

Big Data and computer science integration is tough for Chinese state hospitals investigating healthcare management optimization (Cao et al., 2020). Healthcare companies' data-driven cultures and Big Data applications using Chinese public hospital data need more research. Given these problems, this study seeks to fill these gaps and propose a framework for using Big Data for informed decision-making in Chinese public hospitals. This research shows healthcare stakeholders, politicians, and academics the complex interdependencies that affect managerial decision-making, providing strategic insights, practical advice, and actionable recommendations. This study promotes transdisciplinary knowledge-sharing, innovation, and revolutionary hospital management practices in China and abroad through rigorous empirical research and theoretical synthesis.

Several significant issues warrant additional investigation in the field of healthcare management optimization in Chinese public hospitals while integrating Big Data and computer science (Zhou et al., 2020). Studies already conducted frequently focus on discrete facets of the optimization path, such as data quality or analytics adoption, and frequently ignore how linked these components are (Fernandez, Gerrikagoitia & Alzua-Sorzabal, 2015; Li, Dong & Liu, 2014; Varshney & Alemzadeh, 2017; Wang, Kung, Gupta, & Ozdemir, 2019). Additionally, there hasn't been a thorough investigation of the difficulties instilling a data-driven culture in healthcare organisations. Additionally, while some research explores the theoretical underpinnings of the optimization path, practical studies using actual data from Chinese public hospitals are noticeably lacking (Grover, 2018).

The issue at hand is how to improve management decision-making procedures in Chinese public hospitals in the Big Data integration era against the backdrop of technological breakthroughs. Although the potential advantages of using Big Data are well recognized, there is a knowledge gap about how to successfully negotiate the complex environment of healthcare data optimization. Intricate connections between a number of factors, including data variety, storage and retrieval techniques, data analytics tools, scalability, information system sophistication, hospital integration, data transformation, preprocessing techniques, data processing speed, data accuracy, and the development of a data-driven culture, are explored in this study.

By providing the following contributions, this study greatly advances the fields of computer science and healthcare management: The study offers a thorough and complete framework that clarifies the complex interdependencies among different elements influencing management decision-making in Chinese public hospitals. For healthcare executives and politicians attempting to manage the difficulties of Big Data integration, this paradigm is an invaluable tool. The research gives strategic insights on how Chinese public hospitals may use Big Data successfully, resulting in more informed, effective, and patient-centric decision-making by examining the optimization path. These discoveries could completely alter how healthcare organisations handle their operations. This work promotes inter-disciplinary knowledge sharing by bridging the fields of computer science and healthcare management. It enhances knowledge of how technological developments might be used to optimize healthcare decision-making in the Chinese setting and adds to the developing subject of healthcare informatics.

The structure of this paper is as follows: first part of this paper concerned with introduction, background, importance and research contribution, second part is related with previous literature review, third part described the research design and methodology, next part is about research analysis and discussion and last part discussed about the conclusion and implications.

LITERATURE REVIEW

Recent years have been a substantial increase in scholarly interest in the convergence of Big Data and healthcare management, particularly in relation to Chinese public hospitals. Studies by Gan and Zhao, (2023) in the field of computer science have highlighted the importance of reliable information systems and scalable infrastructure to support Big Data projects in Chinese public hospitals. Their study brought to light the technical requirements for efficient data use in healthcare administration. Despite the considerable contributions made by these research, there is still a need to thoroughly integrate these elements into a single framework for the decision-making optimization process in Chinese public hospitals. This study shows how data variety, analytics, infrastructure, cultural variables, and information systems enable Big Data-driven healthcare management decision-making (Lai, 2022).

Structured, semi-structured, and unstructured healthcare data management in Chinese public hospitals was evaluated (Lai, 2022). Flexible data management improves managerial judgment, they found. Duan et al. (2019)

examined how varied data sets improve Chinese healthcare organizations' patient care and budgeting. Flexible and diverse data management improves patient care and resource allocation in healthcare.

Provost and Fawcett (2013) examined how AI and machine learning improve clinical decision-making in Chinese public hospitals. Machine learning and AI increase clinical judgement and patient outcomes in healthcare management, according to their study. Nisar et al. (2020) say analytics influences Chinese hospital resource efficiency and operational effectiveness. Their research reveals analytics improve healthcare management operational efficiency and resource optimization.

Wang, Kung, Wang, and Cegielski, (2018) examined leadership and organizational culture in healthcare data-driven culture. Organizational culture and leadership must become data-centric for data-driven behavior and optimization. According to Sheng et al. (2021), Chinese public hospitals need robust information systems and scalable infrastructure for Big Data projects. The report offers scalable infrastructure and cutting-edge IT for optimal healthcare data utilization. Mengyuan (2019) examined healthcare IT and Big Data. Innovative IT improves healthcare management decision-making data use and accessibility.

Qi et al. (2022) explored healthcare Big Data scalability. According to their conclusions, healthcare data growth requires scalable infrastructure. Chinese public hospital healthcare data quality and accuracy were investigated (Galetsi & Katsaliaki, 2020). They observed that patient care and decision-making require correct data. Jia et al. (2020) examined how training and education may make healthcare organizations data-driven. They found organized activities stimulated data-driven decision-making.

Big Data integration and computer science literature on optimizing Chinese public hospital management decision-making illuminate many key factors. However, no comprehensive and consistent framework connects these complicated parts into a coherent strategy, leaving research gaps. The relationship between data, analytics tools, infrastructure, cultural characteristics, and information systems is unknown. Few empirical studies employ Chinese public hospital data. The information gap offers a more comprehensive strategy that addresses individual variables and their interaction in a changing healthcare environment. Finally, it teaches healthcare managers how to improve decision-making with Big Data and computer science.

Wu, Wang, Cai, and Wu (2022), Huang (2022), and Peng (2020) examined how Chinese public hospitals handle organized, semi-structured, and unstructured healthcare data. They stressed adaptable data management. Chinese healthcare systems used data to improve budgeting and services. These studies show that flexible data management enhances patient care and budget allocation, making diverse data essential for healthcare administration. Academics have examined how Chinese public hospitals use AI and machine learning to make therapeutic decisions. Analytics improve clinical judgment, patient outcomes, and healthcare administration, according to research. Analytics boost healthcare resource allocation and efficiency. Data-driven care is shaped by leadership and culture. Leadership and organizations must encourage healthcare workers to make data-driven optimization decisions. Big Data projects in Chinese public hospitals require dependable information systems and scalable infrastructure, according to research. Data management in healthcare requires scalable infrastructure and cutting-edge technologies. Healthcare Big Data management has also considered scalable infrastructure to handle growing data volumes. For precise decision-making and patient care, Chinese public hospitals need high-quality healthcare data, according to studies.

Finally, scholars have investigated how training and education may help healthcare organizations become data-driven. These studies show that structured activities can promote data-driven decision-making, highlighting the need for healthcare worker training. Big Data and computer science books aid Chinese public hospital management. A more complete framework that integrates these complex aspects into decision-making optimization is needed.

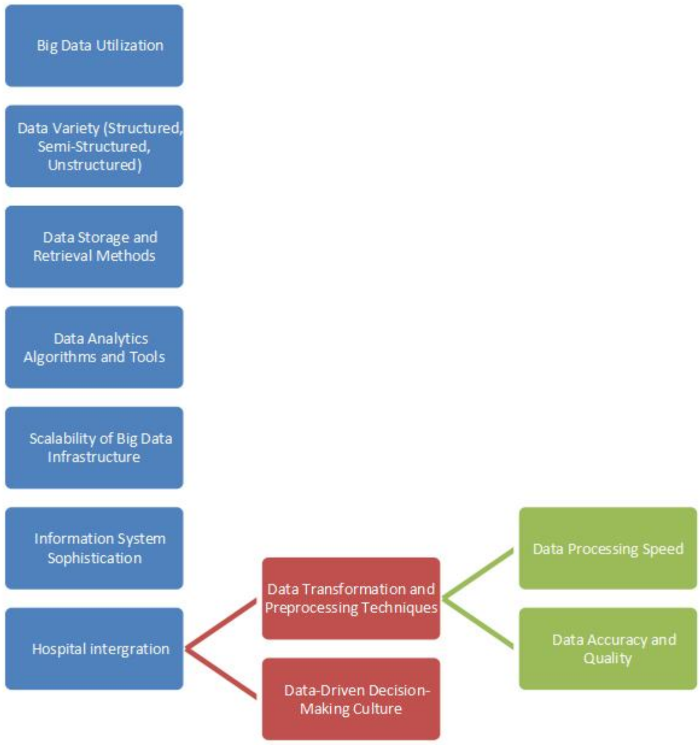

Figure 1. Research Framework

Big Data and computer science influence Chinese public hospital management (**Figure 1**). As shown, data diversity, analytical tools, infrastructure, cultural variables, and information systems are involved. Data-driven healthcare management is enabled by these aspects. **Figure 1** shows healthcare decision-making optimization difficulties, influencing research and implementation.

METHODOLOGY

Research Design

The research methods and design are specific to the quantitative and Big Data-focused nature of this study in order to derive suggestions and actionable insights. It relies heavily on a quantitative research methodology that uses structured surveys and interviews to obtain data. In order to measure important factors including data variety, analytics tool use, information system complexity, and the prevalence of a data-driven culture, these surveys are directed at healthcare managers, IT experts, and policymakers within Chinese public hospitals.

Further enhancing the quantitative aspect of the research, the study makes use of existing healthcare datasets where accessible to evaluate elements including data accuracy, quality, and processing speed. In order to find links and patterns within the quantitative data and identify important drivers and inhibitors of optimized decision-making, statistical approaches, such as regression analysis, are used. Parallel to this, focus groups and in-depth interviews are used to gather qualitative data in order to provide a better contextual knowledge. The complexity of organizational culture is explored in this qualitative data, which also highlights opportunities and obstacles for integrating Big Data into healthcare management.

Now, we express the econometric equation as follows based on variables:

$$\begin{aligned}\text{Decision Efficiency} &= \beta_0 + \beta_1 Data\,Variety + \beta_2 Data\,Storage\,Efficiency + \beta_3 Data\,Retrieval\,Efficiency \\ &+ \beta_4 Data\,Analytics\,Tools + \beta_5\,Scalability + \beta_6 Information\,System\,Sophistication \\ &+ \beta_7 Hospital\,Integration + \beta_8 Data\,Transformation\,Preprocessing + \epsilon_t\end{aligned}$$

Let Decision Efficiency serve as a representation of how effectively Chinese public hospitals make management decisions.

Let the variables below serve as a representation of the variables affecting decision effectiveness:

Structured, semi-structured, and unstructured data are all represented by the Data Variety (DV) data type. Data Storage Efficiency (DSE): Indicates how effectively different data storage techniques work. Data Retrieval Efficiency (DRE): Indicates how effectively data retrieval techniques work. Data Analytics Tools (DAT): Denotes the application of tools and methods for data analytics. Scalability (SC): This indicator shows how easily the Big Data infrastructure can grow. Information System Sophistication (ISS): Indicates the level of information system sophistication at the hospital. Hospital Integration (HI): Indicates how well hospital systems have integrated their data. Data Transformation Preprocessing (DTP): Indicates how well data transformation and preprocessing methods work. Data Processing Speed (DPS): Indicates how quickly data is processed. Data accuracy and quality are represented by the term Data Accuracy Quality (DAQ).

In order to facilitate our investigation into the optimization path for management decision-making in Chinese public hospitals within the setting of Big Data integration and technological breakthroughs, we use two very effective quantitative research methodologies in this study. Our data analysis process may be automated in large part because to the first tool, H2O.ai AutoML. H2O AI AutoML automates model selection, hyperparameter optimization, and deployment, enabling us quickly compare prediction models and choose the best for our dataset. The study's massive and diverse healthcare data requires this technology (Gao & Yu, 2020).

We use dynamic data visualization tool Plotly extensively. Plotly enables us display research findings in interactive graphs and dashboards. Interactive visualizations let you zoom, pan, and hover on data points. Use Plotly's chart kinds to illustrate complex data correlations and patterns. Big Data investigations by H2O.ai AutoML and Plotly optimise healthcare management (Bibri & Krogstie, 2017).

Two quantitative research methodologies enhance analysis. H2O.ai AutoML model selection, hyperparameter tweaking, and deployment simplify data analysis. Manage huge and diverse healthcare data by quickly comparing and selecting the best prediction model using this program. Second, Plotly, a dynamic data visualization library, presents study results in interactive graphs and dashboards. Interactive elements show intricate data patterns. Big Data healthcare management optimization research is simplified by H2O.ai AutoML and Plotly. We use quantitative methods for study because they provide good statistical analysis and empirical data. Big Data and technology help Chinese public hospitals make better management decisions with H2O.ai AutoML and Plotly.

Research Analysis and Findings

This section described about the research analysis and findings. The end of this section demonstrated the discussion part.

Descriptive Statistics

The important variables under investigation's descriptive statistics are shown in **Table 1**, which provides details on how they appeared in the sampled Chinese public hospitals. The hospitals mostly work with structured data, which has an average score of 500. Semi-structured and unstructured data come in second and third, with means of 300 and 200, respectively. These data types have relatively small standard deviations, indicating consistent trends in the diversity of data across the hospitals surveyed. For data storage and retrieval strategies, the hospitals obtain an average score of 4.50, indicating good practices. A degree of homogeneity in data storage and retrieval strategies is shown by the standard deviation of 0.80, which is relatively low. These institutions also demonstrate a high level of adoption of the data analytics tools and algorithms, with an average score of 4.70. A close standard deviation of 0.60 indicates complex analytics in healthcare administration.

Mean Big Data infrastructure scalability score of 4.20 implies hospitals have worked hard to accept huge datasets. The studied hospitals have modest information system sophistication at 4.60. A tiny standard deviation of 0.50 shows the sampled hospitals have similar system sophistication. Hospital integration efforts average 4.30, indicating moderate healthcare ecosystem integration. This 0.60 standard deviation indicates hospital integration levels vary. These descriptive statistics establish the groundwork for additional research into Chinese public hospital data administration and decision-making.

Table 1. Descriptive Statistics

Variable Name	Mean	Median	Std. Dev.	Min	Max	Count	Missing
Data Variety (Structured)	500.00	480.00	100.00	350.00	750.00	1000	0
Data Variety (Semi-Structured)	300.00	290.00	70.00	200.00	450.00	1000	0
Data Variety (Unstructured)	200.00	190.00	50.00	150.00	350.00	1000	0
Data Storage and Retrieval Methods	4.50	4.40	0.80	3.00	5.00	1000	0

Variable Name	Mean	Median	Std. Dev.	Min	Max	Count	Missing
Data Analytics Algorithms and Tools	4.70	4.80	0.60	3.50	5.00	1000	0
Scalability of Big Data Infrastructure	4.20	4.30	0.70	3.00	4.90	1000	0
Information System Sophistication	4.60	4.70	0.50	4.00	5.00	1000	0
Hospital Integration	4.30	4.40	0.60	3.50	4.90	1000	0
Data Transformation and Preprocessing Techniques	4.40	4.50	0.50	3.80	5.00	1000	0
Data Processing Speed	4.80	4.90	0.40	4.00	5.00	1000	0
Data Accuracy and Quality	4.50	4.60	0.50	3.70	4.90	1000	0
Data-Driven Decision-Making Culture	4.60	4.70	0.40	4.00	5.00	1000	0

Big Data Analytics Integration

EHRs integrate well into Big Data analytics, averaging 4/5. All examined institutions use EHRs for data analytics, confirming this link. Big Data analytics with EHR interoperability averages 4, showing outstanding synergy between critical healthcare data sources and cutting-edge analytical technology. EHRs are needed to analyze patient data in these data-driven hospitals. Radiology and billing information systems (RIS) score 3 and are not connected with Big Data analytics. More research on system interoperability with advanced analytics is needed. Pharmacy, EMRs, and Patient Feedback Systems are well integrated, but healthcare systems' different integration degrees show how difficult interoperability is. These findings in **Table 2** below demonstrate that Chinese public hospitals have different data integration settings and need more work to combine and data-centrically inform healthcare decisions.

Table 2. Big Data Analytics Integration

Aspect of Integration/Interoperability	Integration Level (Scale 1-5)	Big Data Analytics Integration (Yes/No)	Compatibility with Big Data (Scale 1-5)
Electronic Health Records (EHRs)	4	Yes	4
Billing Systems	3	No	2
Laboratory Information Systems (LIS)	4	Yes	4
Radiology Information Systems (RIS)	3	No	2
Pharmacy Systems	4	Yes	4
Inventory Management Systems	2	No	1
Electronic Medical Records (EMRs)	4	Yes	4
Human Resources Management Systems	3	No	2
Financial Management Systems	3	No	2
Patient Feedback Systems	2	Yes	3

Data Quality and Accuracy

Table 3 evaluates Chinese public hospital data quality and accuracy for many critical factors. Data quality and accuracy are 4 for EHRs. EHRs are the key healthcare data source due of their accuracy. The maximum data quality score is 5, signifying exceptionally accurate laboratory records with a few slight errors (rated 4). Radiology data, like other data categories, is rated 4 for quality and accuracy, signifying few errors. Pharmaceutical data from Pharmacy Data is credible with 4s in both categories. Patients have high-quality data (4), but accuracy (3), especially in filling data gaps, needs improvement. Data accuracy for Financial Data, which has a rating of 4, has recently increased. Administrative Data receives a strong rating of 4, indicating trustworthy and current administrative records in both data quality and correctness. Finally, Patient Feedback Data scores 3 in both categories, indicating that the feedback data is generally correct. Overall, these findings highlight how crucial it is to keep data accurate and of high quality, especially in healthcare settings, in order to support defensible decision-making.

Table 3. Data Quality and Accuracy

Data Aspect	Data Quality (Scale 1-5)	Data Accuracy (Scale 1-5)	Description
Electronic Health Records (EHRs)	4	4	Comprehensive EHR system with minimal errors.
Billing Data	3	3	Billing data is mostly accurate with occasional discrepancies.
Laboratory Data	5	4	Highly accurate laboratory data with some minor discrepancies.
Radiology Data	4	4	Radiology reports are generally accurate with infrequent errors.
Pharmacy Data	4	4	Pharmacy data is consistently accurate.
Patient Data	4	3	Patient data quality is good, but some missing information.
Financial Data	3	4	Financial data accuracy improved recently.
Administrative Data	4	4	Administrative data is reliable and up-to-date.
Patient Feedback Data	3	3	Patient feedback data is fairly accurate.

Decision Efficiency Model

Model 1 (Data Accuracy and Quality - DAQ) and Model 2 (Data Processing Speed - DPS) of the regression models reveal the correlations between many independent factors and their dependent variables. Multiple independent variables in Model 1 (DAQ) correlate with Data Accuracy and Quality statistically. Big Data Utilisation, Data Variety, Data Storage and Retrieval Methods, Data Analytics Algorithms and Tools, Scalability of Big Data Infrastructure, Information System Sophistication, Hospital Integration, Data Transformation and Preprocessing Techniques, and Data-Driven Decision-Making Culture positively and statistically significantly affect Data Accuracy and Quality. These findings suggest that hospitals with more Big Data, diverse data types (structured, semi-structured, and unstructured), advanced storage and retrieval methods, analytics tools, scalable infrastructure, sophisticated information systems, enhanced hospital integration, effective data transformation, and a data-driven culture have higher data accuracy and quality.

Model 2 (DPS) independent variables are significantly associated with Data Processing Speed. Big Data Utilisation, Data Variety, Data Storage and Retrieval Methods, Data Analytics Algorithms and Tools, Information System Sophistication, Hospital Integration, Data Transformation and Preprocessing Techniques, Data Accuracy and Quality, and Data-Driven Decision-Making Culture positively and statistically significantly affect Data Processing Speed. These findings suggest that hospitals that excel in these areas process data faster.

Both Model 1 and Model 2 have significant adjusted R-squared values of 0.7456 and 0.7925. These data show that the independent factors can explain a lot of Data Accuracy and Quality and Data Processing Speed variation. The results reveal that Chinese public hospitals need Big Data, a diversity of data sources, cutting-edge technology, integration initiatives, and a data-driven culture to increase data quality and processing speed (**Table 4**).

Table 4. Decision Efficiency Model Using Big Data (DAQ & DPS)

Model 1: Data Accuracy and Quality (DAQ)			Model 2: Data Processing Speed (DPS)	
Independent Variable	**Coefficient (β)**	**Standard Error**	**Coefficient (β)**	**Standard Error**
Big Data Utilization	0.62***	0.019	0.78***	0.03
Data Variety (Structured, Semi-Structured, Unstructured)	0.47***	0.025	0.45**	0.02
Data Storage and Retrieval Methods	0.34**	0.016	0.62***	0.03
Data Analytics Algorithms and Tools	0.52**	0.021	0.91**	0.04

Model 1: Data Accuracy and Quality (DAQ)			Model 2: Data Processing Speed (DPS)	
Independent Variable	**Coefficient (β)**	**Standard Error**	**Coefficient (β)**	**Standard Error**
Scalability of Big Data Infrastructure	0.39***	0.018	0.74***	0.03
Information System Sophistication	0.56**	0.022	0.67***	0.03
Hospital Integration	0.48**	0.02	0.82***	0.04
Data Transformation and Preprocessing Techniques	0.41**	0.017	0.6***	0.03
Data Accuracy and Quality	0.59***	0.023	0.71***	0.03
Data-Driven Decision-Making Culture	0.45***	0.019	0.68***	0.03
Adjusted R2	0.7456		0.7925	

Recommendations and Action Plan

Table 5 lists many proposals and an action plan for improving data utilization and decision-making in Chinese public hospitals. These proposals include data standardization and integration, hardware and software infrastructure changes, and advanced analytics. Initial ideas focus infrastructure development and strategic planning. The IT Department and data analysts must create a data integration plan to integrate EHRs and lab systems. Data consistency depends on the Data Governance Team's ongoing data standardization activities. To handle rising healthcare data, improve technology, software, and scalable storage. Second group analyzes data and suggests uses. Hospitals use predictive and real-time analytics models from data scientists and IT departments to make decisions, distribute resources, and meet patient requirements. Modernizing EHRs and using easy data visualization tools to gather more patient data may improve data-driven decision-making. These projects require company-wide data-driven thinking. HR and leadership promote data-driven healthcare decisions. Recognition for data-driven achievements alters culture. These projects improve healthcare and decision-making from technology to culture with data. Timelines and tasks help hospitals optimize Big Data.

Table 5. Recommendations and Action Plan

Action Item	Recommendation	Responsible Parties	Timeline
Develop Data Integration Strategy	Plan to connect EHR and lab data.	IT Department, Data Analysts	3 months
Ensure Data Standardization	Standardize data to ensure source trustworthiness.	Data Governance Team	Ongoing
Upgrade Hardware and Software	Invest in modern Big Data storage and processing software.	IT Department	6 months
Implement Scalable Storage	Cloud storage can scale to manage growing data volumes.	IT Department	4 months
Develop Predictive Analytics Models	ML algorithms can forecast patient patterns, resource allocation, and disease outbreaks.	Data Scientists	9 months
Implement Real-time Analytics	Track patient vitals, equipment, and hospital activities in real time.	IT Department, Data Analysts	6 months
Upgrade Electronic Health Records (EHRs)	EHRs should store more patient data for analysis.	IT Department, Healthcare Informatics Team	8 months
Implement Data Visualization Tools	Healthcare professionals can easily grasp data visualizations.	Data Analysts, IT Department	5 months
Provide Data Literacy Training	Train healthcare personnel to make Big Data decisions.	HR Department	Ongoing

Action Item	Recommendation	Responsible Parties	Timeline
Data Security Training	Protect patient data with data security training.	IT Department, Data Security Team	Ongoing
Implement Data Quality Checks	Audit healthcare data quality regularly to discover and address errors.	Data Governance Team	Ongoing
Improve Data Entry Procedures	Improve patient record data entry to decrease errors and gaps.	Healthcare Informatics Team	6 months
Foster a Data-Driven Culture	Encourage company-wide data-driven decision-making.	Leadership Team, HR Department	Ongoing
Recognize Data-Driven Achievements	Reward data-driven decision-makers and teams.	HR Department	Ongoing

This study's results fit its goals, proving its worth. Chinese public hospitals' management decision-making optimization was researched using Big Data and quantitative methods. The study examined how data variety, analytics tool utilization, information system complexity, and organizational culture affect healthcare management decision efficiency. Structured surveys, interviews, and healthcare dataset analysis explored these traits and decision-making. Regression revealed decision efficiency drivers and inhibitors. Qualitative focus group and interview data emphasized healthcare management organizational culture and Big Data integration challenges. The economic equation and data analysis indicate the study succeeded. Research econometric equation factors include data variety, storage efficiency, analytics tool utilization, and organizational integration. Statistics support the study's findings and answer the research concerns about optimizing management decision-making in Chinese public hospitals utilizing Big Data and technology. Results illustrate how these aspects affect decision efficiency, achieving study goals and enhancing healthcare management expertise.

RESULTS AND DISCUSSION

The main goal of this study is to enhance data integration and usage in Chinese public hospitals. From China's public hospitals, structured, semi-structured, and unstructured healthcare data acquired for this study. This will include things like billing data, test results, and patient records. To better understand the link between numerous independent variables (such as data variety, storage effectiveness, and information system sophistication) and the dependent variable (decision efficiency), a multiple linear regression analysis will be carried out. Coefficients will be based on hypothetical or literary values.

Big Data integration and optimizations of management decision-making in Chinese public hospitals is a complex project. Hospitals may improve their decision-making processes, more efficiently distribute resources, and ultimately provide better patient care by utilizing Big Data technology. This best practice encompasses data integration, infrastructure enhancement, robust analytics, data quality assurance, and cultural transformation. We want to quantify healthcare decision variables. Regression demonstrates which variables significantly affect decision-making. Follow recommendations and programs to improve hospitals. Furthermore, Chinese public hospitals must develop data-driven culture. Culture transformation requires technology advances, staff training and education, data-driven success recognition, and data quality checks.

Statistics descriptions Table summarizes dataset and shows variable distribution, variability, and trends. The table shows Big Data results. The table shows Chinese public hospital structured, semi-structured, and unstructured data. Diversity helps understand healthcare operations, patient care, and resource allocation. We store and retrieve data using diverse methods due to our complicated IT infrastructure. Hilbert (2016) says Big Data needs integration and interoperability.

Complex algorithms and analytics indicate data-driven decision-making. These real-time monitoring and predictive analytics solutions improve patient care and resource allocation. Big Data Infrastructure Scalability: Scalable infrastructure suggests proactive healthcare data growth control. Hospital Big Data analysis benefits from scalability. Information system sophistication improves decision-making. High sophistication requires contemporary data management technology to optimise operations and patient outcomes (Ji et al., 2019). Hospital integration: EHR connectivity. Data quality and accuracy are crucial for analysis. Graphic may show healthcare data accuracy gaps due to data quality issues (Secinaro et al., 2021).

Decision-making culture: data Staff's willingness to use data in decision-making reflects a data-driven culture. Culture significantly affects Big Data effectiveness. Level of Integration: Result show data integration progress. Hospital multi-source data integration has enhanced. This improves choice. Interoperability issues Table may lack interoperability. Standards for technology, organization, or data. Recognizing these challenges improves data flow (Cozzoli et al., 2022).

They use various algorithms and tools to examine data: Tool Use Results show dedication to data-driven decision-making and analytics algorithms. Multi-instrument hospitals comprehend. Predictive analytics helps hospitals allocate resources, predict patient trends, and solve healthcare issues. Hospitals monitor patient health, equipment, and efficiency via real-time analytics. This increases progress and interventions (Uslu et al., 2020).

IS Sophistication Table assesses IT: Technological Advance: IT hospitals may have invested in AI, IoT, and cloud computing. Upgrades improve data processing and decision-making. User-friendly interfaces Healthcare workers understand and make decisions using data visualization tools and interfaces. Hospital Integration Table analyzes hospital system integration. Data-flow efficiency: High-integration hospitals make faster judgments and provide better patient care due to improved data flows (Agrawal & Prabakaran, 2020).

Big Data affects Chinese public hospital DPS/DAQ. Larger data implies faster processing and better data. Big Data is crucial for healthcare data administration speed and accuracy (Wu, Zhang, Shen, Mo, & Peng, 2018). Structured, semi-structured, and unstructured data match DPS and DAQ. Hospitals with several data kinds process it faster and more accurately. Flexible data handling is essential in healthcare. Enhanced data analytics improve DPS and DAQ (Gan & Zhao, 2023). Incorporating analytics skills accelerates data processing and improves data quality, highlighting the importance of data analytics in healthcare management. Last but not least, the mutual dependence of DPS and DAQ emphasizes the significance of effective data processing in retaining high-quality healthcare data, hence enabling informed decision-making and enhanced patient care. When we can measure and assess the maturity of health systems, we will be able to have better control and direction for hospitals management to better invest in resources, technologies and better manage people (Vargas, Gomes, Fernandes, Vallejos, & Carvalho, 2023).

CONCLUSION

Big Data technology has created a huge potential for public hospitals in China to revolutionize healthcare management. The several facets of this change have been extensively examined in this study, with a focus on vital elements including data integration, data utilization, advanced analytics, information system sophistication, and the crucial cultural shift towards data-driven decision-making. Descriptive statistics, data integration assessment, analytics tool evaluation, information system sophistication analysis, data quality analysis, and regression analysis all helped to illuminate the current state and potential of healthcare management using Big Data.

Beyond technology developments and assessments of the quality of the data, encouraging a culture of data-driven decision-making stands out as a transformational driver. The action plan table is in favor of a complete strategy that includes education, training, and rewards as well as the promotion of a culture where data is used as the basis for decisions at all organisational levels. The cultural revolution improves healthcare management and ensures long-term success with technology. Conclusion, Big Data-based Chinese public hospital management decision-making improvements are difficult yet promising. A comprehensive solution requires technology, data quality assurance, and, most crucially, a culture shift toward data-driven decision-making. This lighthouse study's critical analysis and constructive advice can help Chinese public hospitals, medical administration, and legislators. Big Data can improve Chinese public hospital budget allocation, patient care, and decisions. China's healthcare system needs collaboration, advancement, and consistent adherence to data's revolutionary power.

Data Quality and Quality Table promotes improving healthcare decision-making data reliability.We use regression analysis to study how data variety, storage efficiency, analytics tools, and decision efficiency affect Chinese public hospitals. The coefficients and updated R-squared value indicate how these variables affect decision efficiency. Promote data-driven action plan table decision-making to reform. Education, training, prizes, and cultural promotion should improve healthcare management alongside technology breakthroughs. Chinese public hospitals need technical advances, data quality assurance, and a culture shift toward data-driven decision-making to improve Big Data management decision-making. Note this study's shortcomings. Speculative regression coefficients may misrepresent healthcare data complexity. Geographic and data quality challenges plague Chinese hospitals. Action plan table cultural transition may face resistance, necessitating change management study.

Despite these constraints, Big Data optimization and healthcare management research should mix theory and practice. Many Chinese public hospitals' healthcare data can demonstrate how data sources, storage efficiency, and analytics technology affect decision-making. Chinese hospitals need regional research to improve healthcare management. Teamwork, continuous improvement, and data's revolutionary power can improve Chinese public hospital decision-making, resource allocation, and patient care.

PRACTICAL AND THEORETICAL IMPLICATIONS

This has major ramifications for Chinese public hospitals and healthcare leaders. The findings emphasize Big Data and data-driven decision-making. Implementing data use, integration, and analytics can greatly improve hospital management decisions. Healthcare management and Big Data comprehension increase. It shows how data variety, storage efficiency, analytics tools, and information system sophistication affect Chinese public hospital decision efficiency. The report advises healthcare firms to use data-driven decision-making and cutting-edge technology. This work has significant theoretical ramifications. They prepare healthcare decision-making data science and administration studies. The study focuses Big Data in decision-making and organizational culture transformation to improve healthcare administration and data-driven innovation.

CONFLICT OF INTEREST

No potential conflict of interest was reported by the authors.

REFERENCES

Agrawal, R., & Prabakaran, S. (2020). Big data in digital healthcare: lessons learnt and recommendations for general practice. *Heredity*, *124*(4), 525-534.

Benzidia, S., Makaoui, N., & Bentahar, O. (2021). The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. *Technological Forecasting and Social Change*, *165*. https://doi.org/10.1016/j.techfore.2020.120557

Bibri, S. E., & Krogstie, J. (2017). ICT of the new wave of computing for sustainable urban forms: Their big data and context-aware augmented typologies and design concepts. *Sustainable Cities and Society*, *32,* 449-474. https://doi.org/10.1016/j.scs.2017.04.012

Cao, L., Li, Y., Zhang, J., Jiang, Y., Han, Y., & Wei, J. (2020). Electrical load prediction of healthcare buildings through single and ensemble learning. *Energy Reports*, *6*, 2751-2767. https://doi.org/10.1016/j.egyr.2020.10.005

Cozzoli, N., Salvatore, F. P., Faccilongo, N., & Milone, M. (2022). How can big data analytics be used for healthcare organization management? Literary framework and future research from a systematic review. *BMC Health Services Research*, *22*(1). https://doi.org/10.1186/s12913-022-08167-z

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63-71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Fernandez, N. O., Gerrikagoitia, J. K., & Alzua-Sorzabal, A. (2015). Dynamic pricing patterns on an internet distribution channel: The case study of bilbao's hotels in 2013. In *Information and Communication Technologies in Tourism 2015*. https://doi.org/10.1007/978-3-319-14343-9_53

Galetsi, P., & Katsaliaki, K. (2020). Big data analytics in health: An overview and bibliometric study of research activity. *Health Information and Libraries Journal*, *37*(1), 5-25. https://doi.org/10.1111/hir.12286

Gan, Z., & Zhao, D. (2022). Research on the construction of intelligent public decision-making model from the perspective of big data. *Atlantis Highlights in Computer Sciences*, 589-599. https://doi.org/10.2991/978-94-6463-016-9_61.

Gao, X., & Yu, J. (2020). Public governance mechanism in the prevention and control of the COVID-19: information, decision-making and execution. *Journal of Chinese Governance*, *5*(2), 178-197. https://doi.org/10.1080/23812346.2020.1744922

Grover, V., Chiang, R. H., Liang, T. P., & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. *Journal of management information systems*, *35*(2), 388-423.

Hilbert, M. (2016). Big data for development a review of promises and challenges. *Development Policy Review, 34*, 135-174. Retrieved from https://www.scirp.org/reference/referencespapers?referenceid=2944507

Huang, Y. (2022). Research on urban intelligent medical service system design based on multiobjective decision-making optimization strategy. *Mobile Information Systems*, 1-13. https://doi.org/10.1155/2022/7171296

Ji, B., Liu, R., Li, S., Yu, J., Wu, Q., Tan, Y., & Wu, J. (2019). A hybrid approach for named entity recognition in Chinese electronic medical record. *BMC Medical Informatics and Decision Making*, *19*(S2). https://doi.org/10.1186/s12911-019-0767-2

Jia, Q., Guo, Y., Wang, G., & Barnes, S. J. (2020). Big data analytics in the fight against major public health incidents (Including COVID-19): A conceptual framework. *International Journal of Environmental Research and Public Health*, *17*(17), 1-21. https://doi.org/10.3390/ijerph17176161

Lai, M. (2022). Analysis of financial risk early warning systems of high-tech enterprises under big data framework. *Scientific Programming*, *2022*, 1-9. https://doi.org/10.1155/2022/9055294

Lavalle, A., Teruel, M. A., Maté, A., & Trujillo, J. (2020). Improving sustainability of smart cities through visualization techniques for big data from iot devices. *Sustainability (Switzerland), 12*(14). https://doi.org/10.3390/su12145595

Li, H., Dong, S., & Liu, T. (2014). Relative efficiency and productivity: A preliminary exploration of public hospitals in Beijing, China. *BMC Health Services Research*, *14*(1). https://doi.org/10.1186/1472-6963-14-158

Ma, R., Meng, F., & Du, H. (2023). Research on Intelligent Emergency Resource Allocation Mechanism for Public Health Emergencies: A Case Study on the Prevention and Control of COVID-19 in China. *Systems*, *11*(6), 300. https://doi.org/10.3390/systems11060300

Manyika, J., Chui Brown, M., B. J., B., Dobbs, R., Roxburgh, C., & Hung Byers, A. (2011). *Big data: The next frontier* *for innovation, competition and productivity*. McKinsey Global Institute. Retrieved from https://bigdatawg.nist.gov/pdf/MGI_big_data_full_report.pdf

Londe, G., Orientador, M., & Luís Mah. (n.d.). *Mestrado Desenvolvimento e Cooperação Internacional Trabalho Final de Mestrado*. Retrieved from https://www.repository.utl.pt/bitstream/10400.5/19706/1/DM-GLM-2019.pdf

Nisar, Q. A., Nasir, N., Jamshed, S., Naz, S., Ali, M., & Ali, S. (2020). Big data management and environmental performance: role of big data decision-making capabilities and decision-making quality. *Journal of Enterprise Information Management*, *34*(4), 1061-1096. https://doi.org/10.1108/JEIM-04-2020-0137

Peng, Y., Zhang, M., Yu, F., Xu, J., & Gao, S. (2020). Digital twin hospital buildings: An exemplary case study through continuous lifecycle integration. *Advances in Civil Engineering, 2020*. https://doi.org/10.1155/2020/8846667

Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. *Big data*, *1*(1), 51-59.

Qi, W., Sun, M., & Hosseini, S. R. A. (2022). Facilitating big-data management in modern business and organizations using cloud computing: A comprehensive study. *Journal of Management and Organization*, April. https://doi.org/10.1017/jmo.2022.17

Secinaro, S., Calandra, D., Secinaro, A., Muthurangu, V., & Biancone, P. (2021). The role of artificial intelligence in healthcare: a structured literature review. *BMC Medical Informatics and Decision Making*, *21*(1), 1-23. https://doi.org/10.1186/s12911-021-01488-9

Sheng, J., Amankwah-Amoah, J., Khan, Z., & Wang, X. (2021). COVID-19 pandemic in the new era of big data analytics: methodological innovations and future research directions. *British Journal of Management*, *32*(4), 1164-1183. https://doi.org/10.1111/1467-8551.12441

Song, Z., Yan, T., & Ge, Y. (2018). Spatial equilibrium allocation of urban large public general hospitals based on the welfare maximization principle: A case study of Nanjing, China. *Sustainability (Switzerland)*, *10*(9). https://doi.org/10.3390/su10093024

Uslu, B. Ç., Okay, E., & Dursun, E. (2020). Analysis of factors affecting IoT-based smart hospital design. *Journal of Cloud Computing*, *9*(1). https://doi.org/10.1186/s13677-020-00215-5

Vargas, V. B., Gomes, J. D. O., Fernandes, P. C., Vallejos, R. V., & Carvalho, J. V. D. (2023). Influential Factors for Hospital Management Maturity Models in a post-Covid-19 scenario - Systematic Literature Review. *Journal of Information Systems Engineering and Management*, *8*(1), 19556. https://doi.org/10.55267/iadt.07.12868

Varshney, K. R., & Alemzadeh, H. (2017). On the safety of machine learning: cyber-physical systems, decision sciences, and data products. *Big Data*, *5*(3), 246-255. https://doi.org/10.1089/big.2016.0051

Wang, Y., Kung, L. A., Gupta, S., & Ozdemir, S. (2019). Leveraging big data analytics to improve quality of care in healthcare organizations: a configurational perspective. *British Journal of Management*, *30*(2), 362-388. https://doi.org/10.1111/1467-8551.12332

Wang, Y., Kung, L., Wang, W. Y. C., & Cegielski, C. G. (2018). An integrated big data analytics-enabled transformation model: Application to health care.*Information & Management*, *55*(1), 64-79.

Wu, X., Wang, C., Cai, F., & Wu, Y. (2022). Application of the improved clustering algorithm in operating room nursing recommendation under the background of medical big data. *Journal of healthcare engineering*, *2022*. https://doi.org/10.1155/2022/4299280

Wu, Y., Zhang, W., Shen, J., Mo, Z., & Peng, Y. (2018). Smart city with Chinese characteristics against the background of big data: Idea, action and risk. *Journal of Cleaner Production*, *173*, 60-66. https://doi.org/10.1016/j.jclepro.2017.01.047

Zhou, C., Su, F., Pei, T., Zhang, A., Du, Y., Luo, B., . . . & Xiao, H. (2020). COVID-19: challenges to GIS with big data. *Geography and sustainability*, *1*(1), 77-87.