

Understanding the Physicians' Usage Intention of Big Data Analysis in Decision-Making

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ABSTRACT

The advancement of technology has led to an increase in the use of Big Data Analytics (BDA) in healthcare, particularly in hospitals. BDA is used to analyze large volumes of data to improve healthcare outcomes and hospital efficiency. Despite its benefits, many doctors are hesitant to adopt BDA. This study aims to identify the factors that influence doctors' decisions to use BDA by applying the Individual Technology-Organization-Environment (I-TOE) framework, an adaptation of the original TOE model. Through a survey and structural equation modeling (SEM), the study will explore barriers and motivators for BDA adoption, providing insights for hospital administrators and policymakers.

Keywords: Big data analytics (BDA), electronic health record (EHR), decision-making in healthcare, individuals-technology-organization-environment model. (I-TOE).

INTRODUCTION

Scholars have explored the use of Big Data Analytics (BDA) across different sectors. However, in healthcare, its adoption remains relatively low compared to other industries. One of the biggest hurdles to using big data in healthcare is the privacy concern around personal medical records. These concerns make it tough to access and share critical patient information, which complicates the adoption process (Lee & Yoon, 2017). It is crucial for hospitals to efficiently utilize limited medical resources, deliver effective services, and adequately manage the rights and interests of users. As a result of technological advancements, hospitals are increasingly leveraging the potential of BDA to make sense of the large amounts of data they generate daily. The most widely utilized application of BDA in healthcare is the Electronic Health Record (EHR) system. EHRs allow healthcare providers from different departments to access and update patient records seamlessly, thus enhancing clinical efficiency and preventing redundant documentation. BDA data sources in healthcare include patient medical records, hospital records, medical examination results, and information collected by healthcare databases. Galetsi and Katsaliaki (2020) clarified how BDA is employed in healthcare facilities, focusing on its use in diagnosing, preventing, and treating diseases. Similarly, Bates et al. (2014) demonstrated that integrating EHR in primary care hospitals can result in a net financial benefit, reduced costs, or improved revenues. BDA can revolutionize healthcare by helping doctors make more accurate diagnoses.

By utilizing big data, physicians can uncover the social and contextual factors influencing their decisions. BDA provides a deeper understanding of the influences that shape medical practice, such as peer recommendations, regulatory constraints, and the availability of institutional resources. For instance, doctors might be guided by treatment approaches favored by colleagues or by policies set by healthcare regulators, while limited resources could also shape their choice of diagnostic tools. In addition, the data can provide insights into how patients interact with their care team, how technology can be used to improve patient outcomes, and the effectiveness of various treatments. These factors can collectively affect physicians' decisions, and a comprehensive data analysis can help physicians understand how to best utilize BDA for decision-making in their practice. By taking advantage of BDA, physicians can gain valuable insights into the factors influencing their decisions and use this information to inform their decision-making processes.

This study explores how individual factors influence technology adoption, with a focus on cloud computing implementation in Taiwanese hospitals. Using the TOE framework (Tornatzky & Fleischer, 1990) and the I-TOE model (Rosli et al., 2012), we examine how technology, organizational, environmental, and individual factors affect physicians' willingness to adopt big data analytics. By exploring these dimensions, the research seeks to provide insights into the key factors that shape physicians' adoption of big data analytics in the healthcare setting, ultimately contributing to the understanding of technology adoption decision-making processes in the medical field.

THEORETICAL BACKGROUND

Through reviewing literature on enterprise BDA adoption, healthcare Information Technology (IT), BDA applications, we have developed a framework tailored to hospitals. The Information System Success (ISS) Model was proposed by DeLone and McLean in 1992, identifying six ISS dimensions: System Quality, Information Quality, Use, User Satisfaction, Individual Impact, and Organizational Impact. Pai and Huang (2011) proposed a conceptual model suitable for medical information systems by combining the Technology Acceptance Model (TAM) with ISS and extending it to medical information systems by adopting the information quality, service quality, and system quality dimensions. This literature highlights several critical success factors for effectively implementing health information systems in hospitals, which can vary based on the specific hospital system, users, organizational structure, and hospital size. As big data grows, the application of BDA in healthcare is also gradually increasing, such as patient diagnosis, rapid identification of epidemics, and improved patient management. Galetsi and Katsaliaki (2020) emphasize that BDA is transforming healthcare, enabling more precise patient outcomes and streamlined care processes. (They highlight its crucial role in patient diagnosis, rapid identification of epidemics, and improved patient management.) Predictive models, machine learning, visualization, and other methods are used to analyze patient outcomes. The broadening scope of BDA research reflects the complex and varied ways this technology can be applied across the medical field.

Several studies have demonstrated the relevant applications of BDA in healthcare. For instance, Bates et al. (2014) introduced six examples of high-cost healthcare patients and how to reduce risk and cost using big data. This study highlights the potential of wearable technology and machine learning to revolutionize real-time monitoring and treatment efficiency. Medical data differs from general enterprise data due to its fragmented nature. Hospital information systems, insurance databases, and research platforms often hold isolated data, lacking a cohesive integration strategy. Due to the involvement of personnel, the use of expensive equipment, and the potential patient discomfort, the cost of big data can be high (Lee & Yoon, 2017). The advantage of BDA lies in finding correlations and increasing healthcare value. BDA enhances healthcare by optimizing patient outcomes, minimizing resource use, and increasing overall healthcare value.

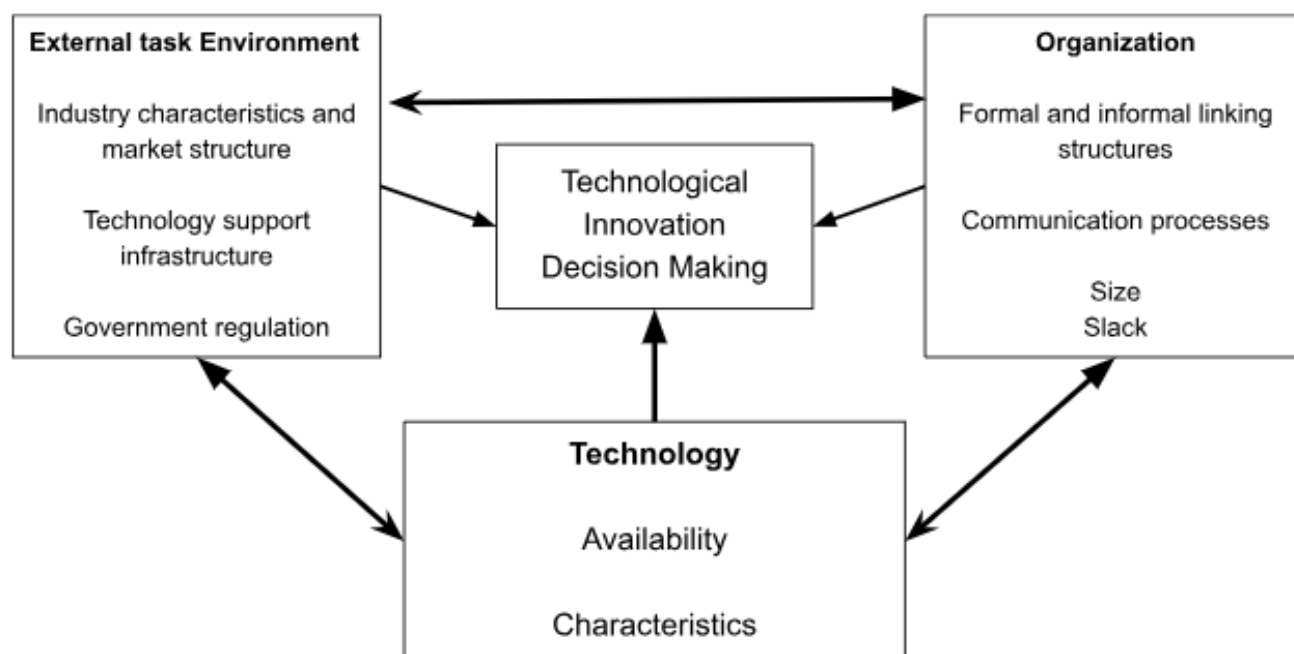
Kim and Park (2017) further studied the critical factors for implementing and applying big data in healthcare, dividing them into four dimensions (technical, data, organizational, and support). They discussed how reducing costs and predicting diseases can benefit healthcare organizations. While Kim and Park focused on the healthcare sector, Maroufkhani et al. (2020) extended the exploration of BDA to small and medium-sized enterprises (SMEs), examining how its adoption impacts their marketing and financial performance. Khanra et al. (2020) categorized the applications of BDA in healthcare into five primary themes: health awareness, healthcare ecosystem, hospital management, treatment of specific diseases, and healthcare technology, as shown in Table 1 below.

Table 1: Key Themes in the Application of Big Data Analytics in Healthcare

Theme	Description
Health Awareness	By analyzing health trends and providing targeted health education, it becomes easier to improve disease prevention and overall health awareness
Healthcare Ecosystem	Better management and optimization of relationships and resources within the healthcare ecosystem lead to improved coordination and efficiency.
Hospital Management	Operational efficiency, medication assignment, and patient flow management within hospitals can be significantly improved through data-driven insights.
Specific Medical Conditions	For conditions like Alzheimer's, cancer, and diabetes, precise treatments and better patient outcomes are made possible through detailed data analysis.
Technology Aspects	The accuracy of medical diagnoses is enhanced through advanced data analytics and machine learning, especially in e-Health and m-Health applications.

Source: This study.

The TOE model(see Figure 1), introduced by Tornatzky and Fleischer in 1990, looks into the main factors driving businesses—across industries like e-commerce, finance, and healthcare—to adopt new technologies and innovate. Recently, Researchers are now applying this model at the individual level to better understand how personal traits affect tech adoption. This shift enables a deeper examination of how personal traits and context influence adoption behavior, while also testing the TOE model's boundaries and generalizability. (Alkhunaizan & Love, 2012). As mentioned earlier, carefully examining adoption decisions is essential in medical settings because of strict privacy rules and the significant impact they have on patient health.



Source: Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990).

Figure 1: Technology, Organization, and Environment Model

To expand the TOE framework, we introduce the individual-technology-organization-environment (I-TOE) model (Rosli et al., 2012), which includes individual-level evaluation of physicians alongside the technological, managerial, and regulatory factors from the TOE model. Incorporating both organizational and individual perspectives is crucial to fully understand what drives hospital staff to adopt BDA. The research questions probe all five dimensions of the I-TOE model, namely technology, organization, environment, individual traits, and BDA properties. By integrating individual factors into the TOE framework, we enhance its effectiveness when applied to innovations like BDA, particularly in healthcare settings where both organizational and personal factors play key roles.

The User's Perspective

Since healthcare institutions are centered around human interactions, this section of the literature review will focus on studies concerning healthcare personnel, particularly in relation to technology adoption. This approach aims to uncover previously unrecognized factors influencing technology adoption within these settings. The next section explores key studies on how users' perspectives, particularly healthcare personnel, influence the adoption of technology.

The IT capabilities of healthcare personnel play a critical role in determining the adoption of BDA by healthcare institutions. According to Yusof et al. (2008), user barriers may be caused by the user's intentions. For example, suppose a doctor is initially unwilling to use the software or system introduced by the hospital. In such a case, it may be because they only feel they are the service provider. Their daily workload is already difficult to bear, and it takes time to participate in a series of training courses and to operate unfamiliar systems, which will take even more time. Suppose the doctor already possesses some professional abilities, such as information technology and data analysis ability; in that case, he will be more willing to use the new system. Physicians with IT and data analysis skills are more likely to adopt new systems than those without such expertise.

By understanding how technology, organizations, and the environment interact, physicians can leverage data to inform their decision-making processes. Liu (2011) argues that the adoption of hospital information systems heavily depends on the IT capabilities and information systems knowledge of the staff. For healthcare institutions to maximize the potential of BDA, their personnel must possess advanced IT skills and a comprehensive understanding of information systems. Such ability will allow employees to effectively analyze and interpret the data generated by BDA, leading to more informed decision-making and improved business outcomes.

Ojha and Mathur (2016) proposed six key characteristics of big data in healthcare: (1) Volume: Hospitals generate large amounts of clinical data from various departments, which can be leveraged for early detection and prevention of genetic diseases. (2) Velocity: The real-time nature of data can be used to seek doctors' opinions in remote areas, allowing patients anywhere to receive medical care. (3) Variety: The types of data in healthcare are diverse and can be broadly classified as structured, semi-structured, and unstructured, such as blood pressure indices, medical images, electronic forms, monitoring equipment, electronic health records, etc. Different types of data are stored differently for future use. (4) Veracity: Incorrect or outdated healthcare data should be deleted. (5) Validity: Time-related healthcare data is vital in telemedicine, where the time it takes for information

to arrive is critical. Delays in data may result in life-threatening situations. (6) Volatility: Consider how long healthcare data needs to be stored before it loses value over time.

Nelson et al. (2005) also proposed several aspects of data quality that hospitals should pay attention to when using BDA. (1) Accuracy: The volume of big data is enormous, making it difficult to determine the data quality quickly. Therefore, it is crucial to verify the accuracy of the data as much as possible when collecting it. (2) Integrity: The sources of big data are diverse, which can result in complex data with different types and structures. Therefore, it is vital to verify the integrity of the data when collecting it. (3) Velocity: Society and the environment constantly change, so more advanced technology is needed to process data in real-time and avoid obtaining outdated information. (4) Readability: Ensure that the data clearly and accurately conveys its meaning, allowing users to understand its content easily. Since BDA has the potential to transform the way healthcare providers operate, by adopting complex technologies to analyze clinical data, healthcare providers such as physicians can make informed decisions based on the insights generated by big data analytics (Raghupathi & Raghupathi, 2014). Adopting complex technologies to analyze clinical data can improve patient outcomes, provide more efficient healthcare delivery, and give a better understanding of population health trends.

RESEARCH MODEL AND HYPOTHESES

Based on the literature review, while many scholars have studied technology adoption in hospitals, the application of BDA within individual hospital environments remains underexplored.

Technology dimensions

According to Rogers' diffusion theory of innovations (2003), "relative advantage" significantly influences the intention to adopt new technologies. Other researchers show that this advantage can reduce operational costs and promote the integration of advanced IT technologies (Premkumar & Roberts, 1999). The relative advantages of physicians employing BDA include lower operational costs and enhanced work efficiency. Additionally, physicians using BDA can also benefit from early disease detection, effective treatment planning, and data-driven decision-making, ultimately leading to better patient outcomes.

Compatibility assessments examine the fit between the new technology and the adopter's existing technological infrastructure, work practices, skills, values, and broader organizational culture. Bradford and Florin (2003) have highlighted "compatibility" as a critical factor for successfully implementing new technology. Subsequently, Hong et al. (2010) researched how to reduce incompatibilities between the existing system and the latest technology. Their findings revealed that providing sustainable training and establishing standard operating procedures are effective strategies for minimizing incompatibility. Thus, reducing organizational incompatibility significantly increases the likelihood of adopting new technologies.

Technology "complexity" can lead to various management risks, including the challenge of keeping the system operational, the uncertainty of its implications for the company, and the potential for negative repercussions on stakeholders. For instance, Premkumar and Roberts (1999) specifically discovered that the complexity of technology could result in the increased risk of financial losses. It introduces substantial uncertainty in the implementation of new techniques, thereby escalating the risks associated with its adoption. Consequently, it is necessary to lessen complexity when introducing new technologies.

Trialability allows potential adopters to test out the innovation first in their own settings and contexts before deciding whether to adopt it fully. For instance, offering a free software trial can enable users to recognize their necessities before purchasing. Rogers (2003) established the concept of "trialability" and argued that it significantly influences how quickly users adopt an innovation. The higher the perceived trialability of new technology, the more positive the attitude users hold toward adopting it and the greater their willingness to utilize BDA. A software trial could decrease the potential risks of implementing the new EHR system.

The "observability" of the benefits associated with new technology can significantly impact its adoption rate. Research has found that technologies with visible benefits can be easily observed by others and often encourage organizations to adopt them (Hong et al., 2010; Agarwal & Prasad, 1997). This phenomenon, known as observability, is a factor that can significantly influence the rate of adoption of a given technology. The degree of observability users perceive in information technology significantly influences their intention to utilize it. Specifically, the magnitude to which physicians discern the benefits or characteristics of BDA directly impacts the propensity of enterprises or individual users to embrace this innovative technology.

Organizational Dimensions

Hospital accreditation is a process designed to ensure adherence to external standards of patient care and safety. Healthcare organizations, such as hospitals, are evaluated and certified by external accrediting bodies to ensure they meet established benchmarks in quality, safety, and operational excellence. Research suggests that these accreditation criteria significantly influence physicians' adoption of BDA (Sack et al., 2011). The pressure of meeting accreditation standards drives physicians to adopt BDA, helping to maintain the highest levels of patient safety and care quality.

Physicians are pivotal stakeholders for the successful adoption and utilization of big data analytics (BDA) in hospital settings. Recent empirical evidence has uncovered a positive association between hospitals' social responsibility (HSR) initiatives and physicians' actual use of BDA (Smith et al., 2020). Specifically, HSR programs can favorably shape physicians' attitudes towards

leveraging BDA, thereby promoting the implementation of these analytical technologies within healthcare organizations. Moreover, HSR undertakings may facilitate the integration of BDA into medical practice by fostering trust in the technology among physicians and providing necessary resources to enable its adoption. Ultimately, the successful assimilation of BDA, facilitated by HSR initiatives, could culminate in enhanced patient outcomes stemming from improved clinical decision-making informed by data-driven insights. Thus, hospitals need to invest in HSR initiatives to ensure the successful implementation of BDA.

DeLone's (1988) research model proposes "Adequate Resources" for the crucial determinants of successful information systems. For instance, adequate resources in a hospital may include sufficient budget, staffing support, time, training on practical operations and computer skills, and other relevant aspects. The availability of necessary resources enables user access to pertinent information and tools and is also indispensable in assisting physicians in making informed decisions. Furthermore, providing the required resources to complete tasks can help improve the healthcare system's efficiency for BDA (Lian et al., 2014).

Maintaining high data quality should be the priority for big data analytics. Nelson (2005) has identified several factors, such as completeness, accuracy, consistency, timeliness, and relevance, which can significantly affect "Data quality". Kwon et al. (2014) demonstrate that data quality can positively impact users' willingness to adopt BDA in organizations.

Environment Dimensions

Governmental policies and regulations strongly influence IT adoption, as demonstrated by the positive impact of cloud computing on technology decisions (Lian et al., 2014; Sulaiman et al., 2018). Hospitals' adoption of cloud computing is further facilitated by regulatory support.

Striving for enhanced efficiency and accelerated technology deployment, hospital management teams have initiated data transfer and analytical processes to garner pivotal insights. By implementing these processes, hospitals can gain superior comprehension of patient needs, formulate more effective care regimens, and achieve higher predictive accuracy of outcomes (Lian et al., 2014; Sulaiman et al., 2018). Moreover, embracing emerging technologies assists with curtailing costs associated with conventional data infrastructure, enabling hospitals to channel resources toward other domains. Hence, adopting new information systems constitutes a strategic investment for hospital managers seeking to uphold competitiveness and optimize patient care. Having explored the organizational and environmental factors, it is crucial to examine how individual IT proficiency and data analysis capabilities contribute to the successful adoption of BDA in healthcare settings.

Individual Dimensions

Information Technology (IT) can be defined as the use and management of computers, storage, networking, and other physical devices, infrastructure, and processes to create, process, store, and transmit information (Merriam-Webster). Understanding and knowledge of IT are crucial for successfully developing hospital software. Research suggests that employee IT proficiency significantly influences the implementation of information systems in healthcare.

Recent research has found that physicians possess an enhanced understanding of IT, reducing the gap in implementing BDA (Lian et al., 2014). This increased confidence in the operational process is beneficial not only to individual physicians but also to the hospital as a whole. Wamba et al. (2017) identified the ability to effectively utilize BDA and competitively capitalize on a big data environment as a critical skill that can bring long-term success to a hospital.

Data analysis capabilities play a pivotal role in harnessing valuable insights, as Wamba et al. (2017) asserted by exemplifying how data analytical skills and knowledge can confer lasting competitive edges on to hospital systems. These can be defined as the collective skills, knowledge, and expertise possessed by individuals or organizations to effectively acquire, manipulate, and analyze data using appropriate statistical and computational techniques (Sharda et al., 2018).

Extracting insights from data is crucial. Hospitals that develop strong data analysis capabilities can transform raw data into informed decisions, leading to meaningful improvements. More specifically, competent data analysis capacities can substantially transform hospital operations, enabling healthcare institutions to comprehend their patients and workflows better, accurately pinpoint challenges and prospects, and facilitate data-driven decision-making. Therefore, nurturing data analysis competencies among staff emerges as a strategic priority for hospitals vying for success in today's increasingly data-intensive healthcare landscapes.

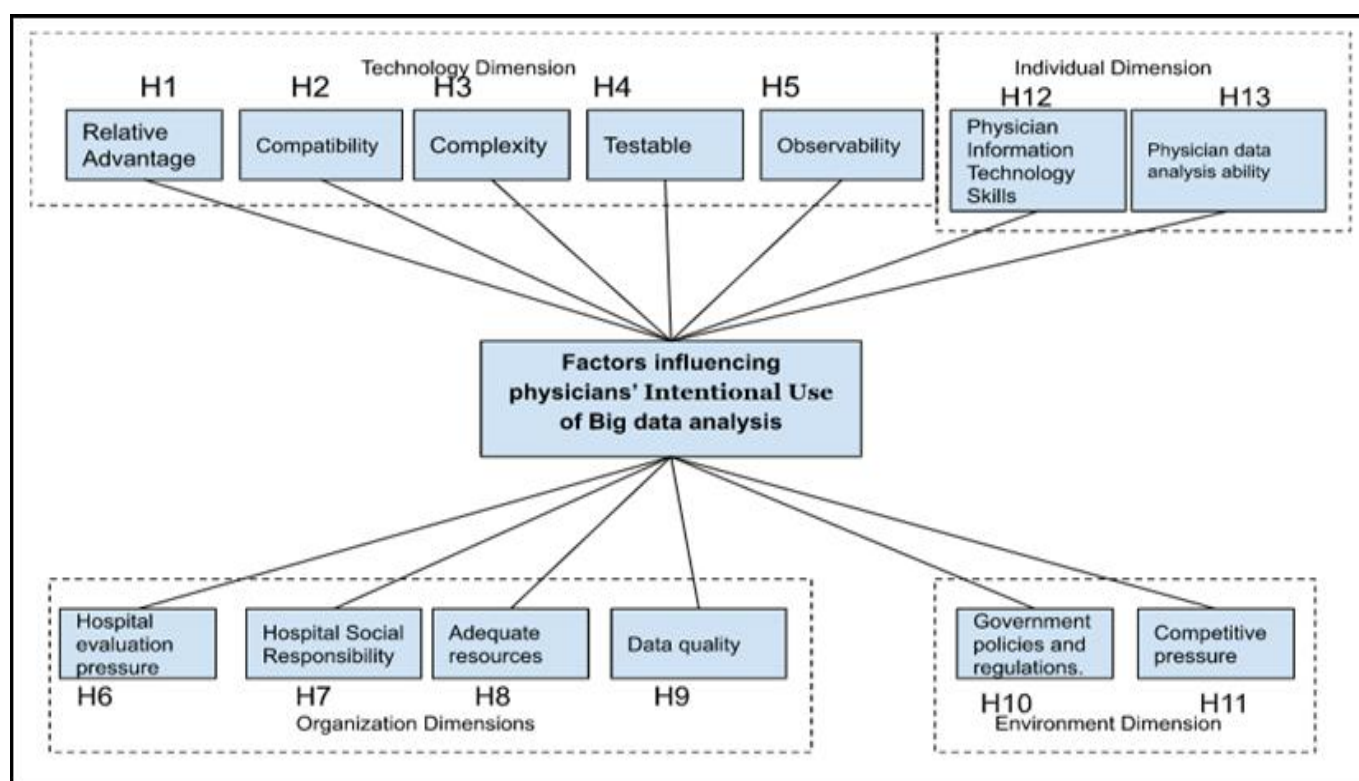
In this study, we expand the original TOE framework by including an individual dimension, the technology dimension, resulting in the I-TOE (Individuals-Technology-Organization-Environment) based research model to explore the user perspective, as shown in Table 2 and Figure 2 below.

Table 2: Research Hypothesis and Literature

Dimension	Hypothesis	Rationale	Literature
Technology	H1: Relative advantage will influence physicians' intention to use BDA.	BDA enables cost-effective healthcare through early disease detection, effective treatment planning, and informed decision-making.	Premkumar & Roberts, 1999
	H2: Compatibility will positively influence physicians' intention to use BDA.	Sustainable training and standard operating procedures effectively minimize incompatibility and increase the likelihood of adopting innovative technology.	Bradford & Florin, 2003; Hong et al., 2010
	H3: Complexity will negatively influence physicians' intention to use BDA.	Reducing complexity is crucial, as it can lead to management challenges and financial risks.	Premkumar & Roberts, 1999
	H4: Trialability will positively influence physicians' intention to use BDA.	A software trial could decrease the potential risks of implementing the new EHR system. Higher trialability leads to more positive attitudes toward adoption and increased willingness to utilize BDA.	Rogers, 2003
	H5: Observability will positively influence physicians' intention to use BDA.	The degree to which physicians discern the benefits or characteristics of BDA directly impacts the propensity of enterprises or individual users to embrace this innovative technology.	Hong et al., 2010; Agarwal & Prasad, 1997
Organization	H6: Hospital accreditation pressure will influence physicians' intention to use BDA.	Accreditation standards enhance the ability to use data analytics technology to help hospitals improve medical quality and gain better control of their services. Accreditation pressure drives physicians to use BDA to maintain patient safety and care standards.	Sack et al., 2011;
	H7: Hospital social responsibility will influence physicians' intention to use BDA.	Hospital social responsibility programs can favorably shape physicians' attitudes towards leveraging BDA, thereby promoting the implementation of these analytical technologies within healthcare organizations.	Smith et al., 2020
	H8: Adequate Resources will positively influence physicians' intention to use BDA.	The availability of necessary resources enables user access to pertinent information and tools and is also indispensable in assisting physicians in making informed decisions. Adequate resources improve the healthcare system's efficiency for BDA.	DeLone, 1988; Lian et al., 2014
	H9: Data quality will positively influence physicians' intention to use BDA.	High data quality positively impacts users' willingness to adopt BDA.	Nelson, 2005; Kwon et al., 2014
Environment	H10: Government policies and regulations will positively influence physicians' intention to use BDA.	Government regulations and policies can actively drive the adoption of IT. As evidenced, hospitals' adoption of cloud computing is facilitated by governmental support through regulations and policies..	Lian et al., 2014; Sulaiman et al., 2018;
	H11: Competitive pressure will positively influence physicians' intention to use BDA.	Competition compelled hospital administrators to implement novel information technologies. Adopting new information systems constitutes a strategic investment for hospital managers seeking to uphold competitiveness and optimize patient care.	Lian et al., 2014; Sulaiman et al., 2018

Individual	H12: Physicians' IT capability will positively influence their intention to use BDA.	Physicians possess an enhanced understanding of IT, reducing the gap in implementing BDA. Effectively utilizing BDA and maximizing the potential of big data is a critical skill for long-term hospital success.	Lian et al., 2014; Wamba et al., 2017
	H13: Physicians' data analysis capability will positively influence physicians' intention to use BDA.	Data analysis capabilities play a pivotal role in harnessing valuable insights. Nurturing data analysis competencies is a strategic priority for hospitals in today's data-intensive healthcare landscape. Competent data analysis capacities can substantially transform hospital operations, enabling healthcare institutions to comprehend their patients and workflows better, accurately pinpoint challenges and prospects, and facilitate data-driven decision-making.	Wamba et al., 2017; Sharda et al., 2018

Source: This study.



Source: This study.
Figure 2: Research Model

METHODS

Measurement Items and Survey

In this study, we collected data through a structured questionnaire with three main sections. The first section gathered basic demographic details about the participants, covering areas like gender, age, education level, hospital location and level, department, and job title. The second section focused on the implementation status of Big Data Analytics (BDA), asking questions about the current stage of BDA integration, system development methods, and the specific tools being used. The final section delved into four key areas—technology, organization, environment, and user experience—using a Five-Point Likert Scale to measure responses, from "1" (strongly disagree) to "5" (strongly agree).

After the initial draft of the research questionnaire was completed, a pre-test and subsequent test were conducted to ensure the reliability and validity of the questionnaire content. During the pre-test phase, nine experts were invited to suggest revisions to the questionnaire and make content adjustments to ensure that the questionnaire content was clear and understandable to the participants, enhancing the reliability and validity of this study. In the second testing phase, twenty experts with extensive hospital work experience were invited to review the questionnaire. Appropriate revisions are made based on their suggestions.

to ensure that the questionnaire survey accurately reflected the actual situation and truly captured the factors that influence doctors' intentions to use big data analysis.

The main interviewees of this study were doctors serving in hospitals, including regional hospitals, district hospitals, and medical centers. This study aimed to understand physicians' use of big data analytics and their intentions behind adopting it, ultimately to encourage hospitals to utilize BDA. Consequently, this was expected to increase the value and contribution of this research. The questionnaire, designed with these goals in mind, was distributed to doctors who had used or may use big data analysis in the future.

We adapted measures from prior research, ensuring that the original meanings were preserved. The measurement items and supporting references are summarized in Table 3 and Table 3.1:

Table 3: The Operational Definition of The Variable

Measuring variables	Operational definition	References
Relative advantage	The adoption of BDA can reduce the physician's operational costs and improve the physician's work efficiency.	Premkumar & Roberts (1999); Rogers (2003);
Compatibility	The degree of compatibility between the adoption of BDA and the hospital's existing IT infrastructure (software, hardware).	Bradford and Florin (2003); Hong et al. (2010);
Complexity	The difficulty level of using and learning BDA.	Premkumar and Roberts (1999);
Testable (Trialability)	The degree to which physicians can test (try out) BDA before using it.	Rogers (2003)
Observability	Whether the benefits of using BDA for the hospital are easy to observe and describe.	Hong et al. (2010); Agarwal and Prasad (1997)
Hospital evaluation pressure	The impact of significantly improving the efficiency of hospital operations and performance with the use of BDA.	Sack et al. (2011)
Hospital social responsibility	The impact of using BDA on pursuing a common vision of the common interest for health care professionals, other stakeholders and the overall society.	Smith et al. (2020)
Adequate resources	The impact of sufficient budget, sufficient human resources support, sufficient time and relevant education and training on/in the adoption of BDA.	DeLone's (1988); Lian et al.(2014)
Data quality	Whether the data integrity, timeliness, readability, and accuracy of BDA have been achieved.	Wamba et al. (2017)
Government policies and regulations	The degree to which the government initiates policies to allocate various resources for the use of BDA in hospitals (including government financial support, training courses, legal norms and policy stability).	Nelson (2005); Kwon et al. (2014)
Competitive pressure	The impact of facing competitive pressure from competitors in the industry when using BDA.	Lian et al. (2014); Sulaiman et al.(2018);
Physician information technology capability	The computer knowledge and technical ability that physicians possess for adopting BDA.	Lian et al. (2014); Sulaiman et al. (2018)
Physician Data analysis capability	The BDA professional ability (such as collective skills, knowledge, and analyze data using appropriate statistical and computational techniques) that physicians possess.	Lian et al.(2014); Wamba et al.(2017) Sharda et al. (2018)
Usage intention	The subjective willingness of physicians to use BDA to handle medical data.	Lian et al.(2014); Liu (2011); Ojha and Mathur (2016); Raghupathi & Raghupathi, (2014)

Source: This study.

Table 3.1: Question Listing

Section	Questions	Dimension
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Relative advantage	1.Using BDA improves communication efficiency with hospital partners. 2.Using BDA reduces operational costs. 3.BDA enhances our hospital's medical quality. 4.BDA increases the profitability of our hospital. 5.BDA provides real-time information for decision-making.	Technology Dimension
Compatibility	1.BDA aligns with our hospital's goals, beliefs, and values. 2.BDA is compatible with existing hardware. 3.BDA is compatible with current software platforms. 4.We have a supportive attitude toward BDA usage. 5.BDA is similar/compatible with previously introduced information systems.	Technology Dimension
Complexity	1.Learning BDA is complex for me. 2.Integrating BDA with my workflow is complex. 3.Developing the BDA system is a complex process.	Technology Dimension
Testable (Trialability)	1.I have sufficient time to test BDA functionalities. 2.The hospital provides a sufficient trial period before adopting BDA.	Technology Dimension
Observability	1.I can easily explain BDA results to others. 2.Competitors or partners have started using BDA. 3.I can observe others in the hospital using BDA. 4.I can discuss BDA outcomes with others.	Technology Dimension
Hospital evaluation pressure	1. I understand the purpose of BDA for hospital accreditation. 2. I understand the impact of BDA on accreditation results and standards. 3.BDA is crucial for accreditation outcomes. 4.BDA relates to accreditation levels. 5.BDA alleviates accreditation pressure by providing real-time updates and forms.	Organization Dimension
Hospital social responsibility	1.I understand the importance of hospital social responsibility. 2.Social responsibility standards should include ethics and social welfare. 3.Hospitals need social responsibility to stay competitive. 4.Hospitals prioritize patient rights over cost. 5.Hospitals value patients' and families' opinions. 6.Hospitals continuously improve service quality to enhance patient satisfaction.	Organization Dimension
Adequate resources	1.The hospital has sufficient resources to support BDA. 2.There is enough time for BDA development. 3.The hospital has an adequate budget for BDA. 4.Sufficient human resources are available for BDA development.	Organization Dimension
Data quality	1.The BDA system's database is updated regularly. 2.The BDA system uses accurate data. 3.The BDA system data is complete. 4.The data in the BDA system meets hospital standards and is easy to understand.	Organization Dimension
Government policies and regulations	1.Government-provided installation fees for BDA increase usage willingness. 2.Government-provided training increases willingness to use BDA. 3.Government regulations and policies encourage BDA usage. 4.Government policy actively encourages us to use BDA. 5.Government incentives (e.g., technical support, training, funding) enhance BDA adoption.	Environment Dimension
Competitive pressure	1.BDA is necessary for staying competitive in the medical industry. 2.Competitors' use of BDA pressures our hospital to adopt it. 3.We actively track competitors' technological innovations.	Environment Dimension
Physician information technology capability	1.I have computer-related knowledge (e.g., programming, basic operations). 2.At least one physician in our hospital is a computer expert. 3.Compared to similar hospitals, our physicians are more knowledgeable about IT. 4. I lack computer-related knowledge (e.g., programming, basic operations).	Individual Dimension
Physician Data analysis capability	1.I am skilled in data analysis. 2.I can quickly learn new data analysis techniques. 3.I understand our hospital's policies and plans. 4.I understand the functions of the hospital's BDA system. 5.I collaborate closely with IT staff to communicate my needs for BDA usage.	Individual Dimension
Usage intention	1.I intend to use BDA within the next year. 2.I plan to use BDA within the next year. 3.I want to use BDA within the next year.	

Source: This study.

Data Collection and Statistics

This study investigated the implementation status of big data analytics (BDA) among physicians across hospitals of different levels, including medical centers, regional hospitals, and district hospitals. A total of 293 questionnaires were distributed, and 276 valid responses were received after excluding 17 invalid samples, resulting in an effective response rate of 94.2%. The demographics of the respondents are reported in Table 4. This sample showed a good representation compared to the national physician age distribution.

Table 4: Sample Size and Percentage of Data Collection

Category	Sample Size	Percentage	Category	Sample Size	Percentage
Age Distribution			Most Responded Medical Department		
20-29 years old	28	10.10%	Internal Medicine	42	15.20%
30-39 years old	74	26.80%	Neurology	28	10.10%
40-49 years old	68	24.60%	Family Medicine	22	8.00%
50-59 years old	59	21.40%	Surgery	17	6.20%
60 years old and above	47	17.00%	Obstetrics Gynecology	15	5.40%
Gender Distribution			Pediatrics	18	6.50%
Male	215	77.90%	Psychiatry	9	3.30%
Female	61	22.10%	Orthopedics	7	2.50%
Education Level			Rehabilitation Medicine	18	6.50%
Bachelor's Degree in Medicine	192	69.60%	Dermatology	7	2.50%
Master's Degree	63	22.80%	Ophthalmology	9	3.30%
Doctoral Degree	21	7.60%	Radiation Oncology	5	1.80%
Hospital Location			Emergency Medicine	19	6.90%
Taipei, New Taipei, Keelung (North)	65	23.60%	Urology	11	4.00%
Taoyuan, Hsinchu, Miaoli (North-Central)	17	6.20%	Otolaryngology	13	4.70%
Taichung, Changhua, Nantou (Central)	54	19.60%	Neurosurgery	2	0.70%
Yunlin, Chiayi, Tainan (South-Central)	76	27.50%	Anesthesiology	8	2.90%
Kaohsiung, Pingtung (South)	58	21.00%	Radiology	8	2.90%
Yilan, Hualien, Taitung (East)	6	2.20%	Anatomical Pathology	5	1.80%
Hospital Level			Clinical Pathology	2	0.70%
Medical Center	117	42.40%	Nuclear Medicine	1	0.40%
Regional Hospital	94	34.10%	Occupational Medicine	1	0.40%
District Hospital	65	23.60%	Plastic Surgery	1	0.40%
BDA Introduction Status			Others	8	2.90%
Introduced	106	38.40%	Job Title		
Being Introduced/Testing	58	21.00%	Attending Physician	124	44.90%
Still Being Evaluated	43	15.60%	Physician as administrator	47	17.00%
Not Introduced	13	4.70%	Chief Physician	44	15.90%
Unclear	56	20	Resident Physician	44	15.90%
BDA Construction Method			PGY Physician	17	6.20%
Self-Developed	41	14			
Outsourced Development	66	23			
Purchased Package Software	66	23			
Unclear	103	37			

Source: This study.

Construct Reliability and Validity

This study used Cronbach's Alpha to test the questionnaire's reliability. Hair et al. (2019) stated that reliability indicates the consistency of the measuring tool, and a Cronbach's Alpha value of 0.7 or above shows a high level of reliability. Values between 0.35 and 0.7 indicate moderate reliability, while researchers classify values less than 0.35 as low. As a result, any items with low reliability were removed from the questionnaire. The Cronbach's Alpha values for all variables in the research framework exceeded 0.6, indicating that the questionnaire was representative.

Validity indicates how a measuring tool accurately measures what its designers intended. This study adopted Content and Construct validity to evaluate the questionnaire's validity. Content validity was assessed through literature review and feedback from 25 experts in medical information.

Construct validity was further divided into convergent and discriminant validity. According to Fornell and Larcker (1981), three criteria for convergent validity are proposed: the standardized factor loadings (Factor Loading) of each item should be greater than 0.5, the composite reliability values (Composite Reliability) should be greater than 0.8, and the average variance extracted values (Average Variance Extracted (AVE) should be greater than 0.5. Discriminant validity mainly measures the extent to which different constructs are unrelated, and the lower the correlation between different constructs, the higher the discriminant validity.

KMO (Kaiser-Meyer-Olkin) and Bartlett's sphericity tests were performed to determine the sample's suitability for factor analysis. Values closer to 1 on the KMO scale indicate higher inter-variable correlations and better suitability for factor analysis, while values closer to 0 suggest a less suitable condition for such analysis. All KMO values in this study exceeded 0.5, indicating that the variables were suitable for factor analysis. We divided the variables into four groups to test the KMO values, including technological, organizational, environmental, data, and user dimension variables, as well as the intention to use big data. Each group had KMO values above 0.5, and Bartlett's sphericity tests were significant, further supporting the appropriateness of the variables for factor analysis.

This study utilized Principal Component Analysis (PCA) to evaluate the construct validity of the questionnaire. PCA converts possibly correlated variables into linearly uncorrelated principal components via orthogonal transformation. It reduces dimensionality by identifying patterns that explain maximum variance. Factor loadings denote the correlation between variables and components. Values above 0.35 signify adequate contribution in explaining a principal component.

Researchers performed varimax rotation to obtain factor loadings. As suggested by Hair et al. (2006), loadings higher than 0.35 demonstrate construct validity, given this study's large sample size (>250). Results showed that all measurement items had factor loadings exceeding 0.35, proving the questionnaire's high construct validity. This study applied structural equation modeling (SEM) to examine the validity of the hypotheses and the relationships among factors. Before the pathway analysis, four critical assumptions of SEM were tested to ensure appropriate model specification and reliable results.

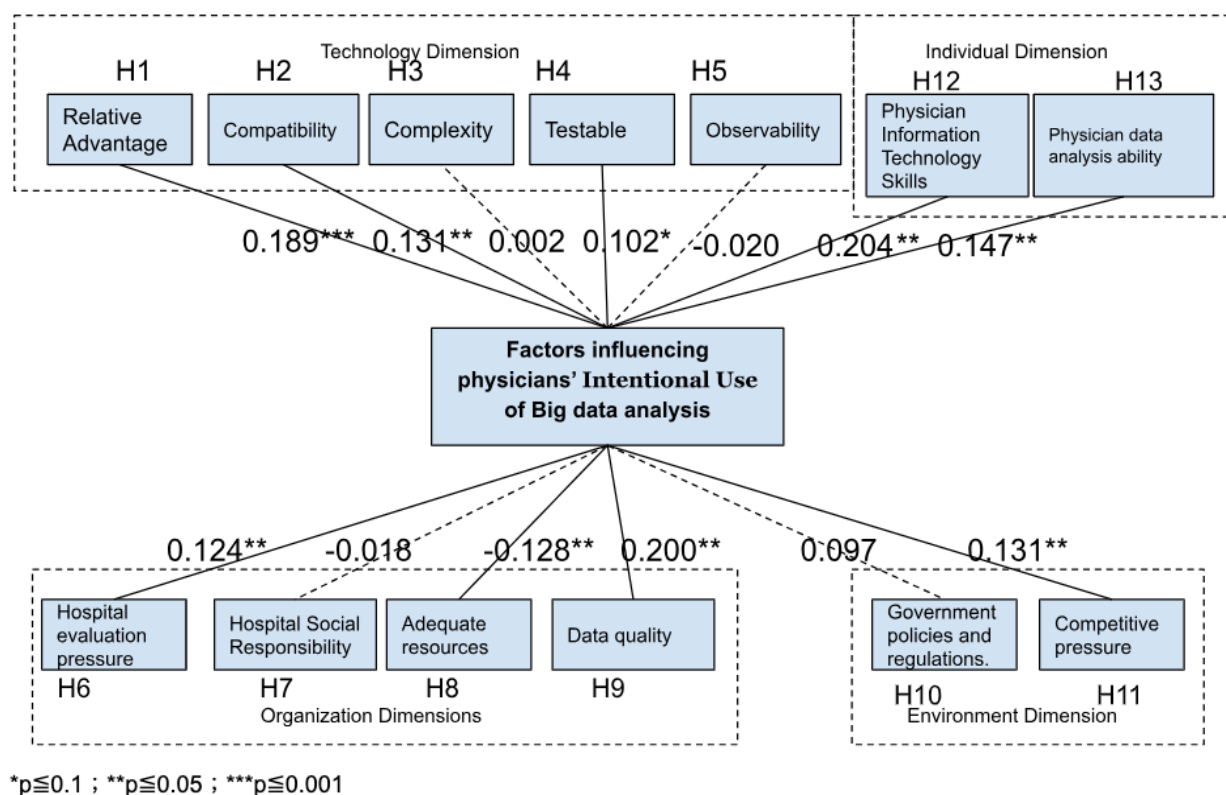
First, normality was assessed using P-P plots. The 45-degree angle of the lines on the P-P plots indicated that the variables were approximately normally distributed, satisfying the normality assumption. Second, multicollinearity was tested by examining variance inflation factors (VIF). The VIF quantifies how much the variance of the estimated regression coefficient is inflated by collinearity. Values greater than ten generally indicate problematic collinearity. Pearson's correlation coefficients were also checked. Correlation greater than 0.8 between independent variables may suggest collinearity issues. In this study, the VIF values were all below 3, and Pearson's correlations were all under 0.8 across variables, indicating that multicollinearity assumptions were fully met. There was no critical collinearity among the independent variables to distort the SEM results. Third, homoscedasticity was checked through scatter plots of the residuals. The residuals are distributed evenly around 0, meeting the homoscedasticity requirement. Finally, Durbin-Watson statistics were calculated to test the independence of error terms. The statistics were close to 2, indicating that the residuals were uncorrelated.

In summary, all four assumptions for SEM were met: normality, multicollinearity, homoscedasticity, and independence of error terms. This ensures an appropriate SEM that yields reliable analysis outcomes. The next step was to assess the structural model fit indices and investigate the path relationships among latent constructs. Following the criteria suggested by Hair et al. (2019) for structural equation modeling. The R^2 value for BDA intention was 0.411, demonstrating strong explanatory power of the model. The standardized path coefficients were used to test the significance of the research hypotheses. This study employed the bootstrapping method to calculate the path coefficients and p-values. The lower the p-value, the stronger the effect of the independent variable on the dependent variable. Of the thirteen hypotheses tested, eight were supported, indicating significant relationships among the key variables. Table 5 and Figure 3 present a comprehensive overview of the Structural Equation Modeling Results..

Table 5: Structural Equation Modeling Results

Hypothesis	Path Coefficient	(p-value)	Hypothesis	Path Coefficient	(p-value)
H1	0.189	0.000***	H7	-0.018	0.759
H2	0.131	0.002**	H8	-0.128	0.049**
H3	0.002	0.968	H9	0.2	0.010**
H4	0.102	0.047**	H10	0.097	0.132
H5	-0.02	0.665	H11	0.131	0.026**
H6	0.124	0.026**	H12	0.204	0.002**
			H13	0.147	0.008**

Source: This study.



Source: This study.
Figure 3: SEM Result

DISCUSSIONS AND CONCLUSION

This study explored the main factors influencing physicians' intention to adopt BDA in hospitals. The findings revealed significant differences between hospitals already implementing BDA systems and those without BDA experience. These results highlight the complex of individual, technological, organizational, and environmental factors that shape physicians' decisions to embrace data-driven analytics in healthcare delivery. Hospitals with BDA systems were most influenced by compatibility, competitive pressure, and data quality. In terms of the variables, hospitals that had introduced BDA were significantly influenced by compatibility, competitive pressure, and data quality. Physicians in hospitals that had not introduced BDA were significantly influenced by relative advantage, trialability, and physician information technology capability. The present study examined the key factors shaping physicians' intention to adopt big data analytics (BDA) in hospital settings. The findings revealed significant differences between hospitals already implementing BDA systems and those without this experience.

These results highlight the complexity of individual, technological, organizational, and environmental factors that shape physicians' decisions to embrace data-driven analytics in healthcare delivery. While prior research has consistently demonstrated the positive roles of perceived benefits, prior experiences, and self-efficacy in fostering technology adoption, this study further reveals how the specific barriers and facilitators may evolve as BDA implementations mature within healthcare organizations. For institutions with integrated BDA workflows, sustaining efforts to enhance system compatibility, optimize data quality, and strengthen analytic capabilities are paramount to extract value, improve patient care, and maintain a competitive edge. Theoretically, these findings lend further empirical support to the Technology-Organization-Environment (TOE) framework by demonstrating how individual attributes (e.g., perceived advantages), technological characteristics (e.g., compatibility), organizational factors (e.g., data quality), and external environmental pressures (e.g., competition) collectively shape physicians' intentions to adopt BDA solutions. This extends the applicability of the TOE model to the healthcare domain and offers a valuable reference for future investigations in this area.

This study has some limitations. The sample was restricted to hospitals within specific geographical regions, potentially limiting the generalizability of the findings. Additionally, the study did not account for physicians' characteristics (e.g., age, experience) that may influence adoption decisions. Future studies should consider cross-role and cross-departmental perspectives using an adapted TOE framework to better understand the factors driving data-driven healthcare transformation.

In conclusion, this study provides actionable insights to facilitate the successful implementation of BDA capabilities in healthcare organizations. By elucidating the key factors impacting physicians' adoption intentions and proposing tailored managerial recommendations based on implementation maturity, hospitals can better leverage data-driven solutions to enhance medical quality, operational efficiency, and, ultimately, patient care experience. Continuous efforts to optimize relevant factors

and implement appropriate change initiatives will be crucial to unlocking the full potential of BDA in transforming healthcare delivery.

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