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-RESEARCH ARTICLE-

THE IMPACT OF BIG DATA UTILIZATION ON MALAYSIAN GOVERNMENT HOSPITAL HEALTHCARE PERFORMANCE

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—Abstract—

The Malaysian healthcare systems face incredible challenges as technology is being used more and more widely, and citizens' expectations are increasing just as rapidly. The Healthcare industry is adopting big data in daily operations to ensure excellent performance. In this context, Big Data can help providers achieve these objectives in an unparalleled manner. However, the Malaysian government hospitals remain unable to implement big data. Hence, this study examines the mediating role of the use of big data (UBD) on the relationship between hospital performance (HP), data quality (DQ), data

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integration (DI), and data governance (DG). The study framework is established from theories, namely Resource-Based View (RBV), extending the DeLone and Mclean IS Success Model (D&M ISSM). The data was collected from Malaysian government hospitals.

Total questionnaires of 560 were distributed, and 212 were responded. The convenience sampling technique was used. Hypotheses tests were performed via Smart PLS 3.3.2. Results show DQ and DI have significant direct relationships with the UBD. However, DG is not significant with UBD. Findings on the use of big data as a mediating variable reveal DQ and DI have a significant direct relationship with UBD except for DG. Findings provide important insights to government, policymaker, and researchers to further understand the use of big data to enhance hospital performance in Malaysia.

Keywords: Hospital Performance; Big data, Malaysian Government Hospital; Resources- Based View; Malaysia

JEL Classification: O32

1. INTRODUCTION

The Coronavirus disease (COVID-19) was sobering to leading healthcare organizations worldwide. In Malaysia, the advanced healthcare system in the country was extended beyond its capacity. When the system's capacity is surpassed, rationing decisions have to be made, extending well beyond COVID-19 patients (Mo et al., 2020; Shahzad et al., 2021). Big data aims to mitigate the impact of an epidemic, reduce health services burdens, protect populations at risk of infectious diseases, and reduce deaths (Agbehadji et al., 2020). Big data evolves into a knowledge ecosystem: a network of internally and externally shared information, automated decisions, outcomes, and new insights for business (Abdelaziz et al., 2018). Big data improves patients to achieve a better and more precise diagnosis and treatment because it helps physicians and other medical practitioners (Pramanik et al., 2017). With enhanced data analysis tools, doctors find approaches for treating rare and severe diseases, which otherwise would seem incurable because research studies advance more rapidly (Li et al., 2018). If Malaysian hospitals can recognize and respond to high-risk patients with customized and patient-centered care, control can be exercised. Using predictive analytics that takes advantage of real-time patient data to generate clinically meaningful information and assist with the right decision-making in the future, there will be fewer visits to the emergency room (Yanshan Wang et al., 2018). Big data can provide continuous and frequent monitoring of health practitioners and Malaysian hospitals to address issues and identify root causes of problems (Mohamed et al., 2020). Big data will reduce healthcare costs, reduce overhead waste and maximize resource usage. It can be used to recognize and respond better to epidemics, cure and manage illness, avoid premature deaths, and enhance citizens' overall quality of life and well-being (Kumar et al., 2020). Data quality, data integration, data governance have a significant relationship with healthcare performance (El Alaoui et al., 2019). Data quality is critical for the reliability of data in decision-making related to patients in healthcare (Hee, 2017). Healthcare produces comprehensive data covering patients, medications, disorders, treatments, studies (Shafqat et al., 2020). Data integration helps to shared information, automated decisions, outcomes and new insights for business (Abdelaziz et al., 2018; Nadal et al., 2019). Data governance helps to avoid security violations and protect patient privacy, the healthcare industry needs to enforce robust data rules and monitoring processes for highly sensitive clinical data (Keshta & Odeh, 2020).

Resource-Based View (RBV) and DeLone and Mclean IS Success Model (D&M ISSM) theories have supported the unique role of the use of big data as a mediating variable in the relationship between data quality, data integration, and data governance, which suggests why, what and how new ideas and technologies are operating at individual and organisation levels (Ghasemaghaei et al., 2018). This study focuses solely on government hospitals in Malaysia and their healthcare performance as a dependent variable.

Five major sections are in this paper. Section 2 briefly explains the important use of big data using the Resource-Based View (RBV) and DeLone and McLean models in a compilatory review of the previous literature. Section 3 focused on a description of the method of investigation and the overall data collection and analysis process. Section 4 deals with an interpretation of the results of measurement variance. Finally, Sect. 5 concluded with a holistic discussion on big data in government hospital performance.

2. LITERATURE REVIEW

Big Data plays a vital role as it can be used in disease outcome prediction, comorbidity detection, mortality, and cost savings (Mehta & Pandit, 2018). In Malaysia, the emphasis has been focused on big data, and some steps have been taken to share medical information and awareness of patients with the government, private hospitals, and clinics (Kalid et al., 2018). Nevertheless, implementing big data in the healthcare industry poses numerous challenges, particularly data protection, standards, governance, data integration, data quality, data classification, technical integration (Mooney & Pejaver, 2018; Shahzad et al., 2020). Most healthcare information is often unstructured and resides in silos in images, medical prescriptions, and clinical notes, insurance claims data (Gangavarapu et al., 2019; Hussain et al., 2020). The organizations have collected unprecedented results from 'limited information' (poor quality data), the lack of standardization in the data field, and several other factors.

Healthcare data typically gathered in the silos of their health centers and regulated and handled by the administrative departments of hospitals or clinics (Parks et al., 2019). The collected data are sometimes silos in hospitals, clinics, and administrative departments managed archives. There needs to be more data integration, such as patient monitoring data, for instance, have not been integrated into clinical diagnoses and therapies in many cases, and clinical data in public health and infectious disease surveillance are not integrated (Shi et al., 2021). Furthermore, integrating medical data and making its analysis efficient and insightful may improve medical results while protecting data privacy and security (Hee, 2017). There are no set requirements or standards, or compliance followed for healthcare details or data creation. The key factor is the influx of technical advancement and constantly changing standards and guidelines (Alkhazali & Hassan, 2015). The existing standards and technologies are insufficient to meet the needs of big data integrative healthcare applications. In addition, it is difficult to integrate different levels of structured, semi-structured, and unstructured data. (Borgogno & Colangelo, 2019).

2.1.1 Healthcare performance

Performance measurement is a tool for the achievement of objectives of the health system. Based on (Liao et al., 2019), hospital performance determining factors are patient waiting time and patient satisfaction. For the hospital directors and policymakers, this has been a significant issue because it measures organizational effectiveness. The key factors impacting patient and customer satisfaction are waiting time and appointment time (Alarcon-Ruiz et al., 2019). Patients must wait at least two hours from registration until they get treatment from doctors in public hospitals in Malaysia (Ting et al., 2019). Effective performance measurement helps an organization assess key processes and effect positive changes to improve care. Three outcomes, such as financial performance, customer satisfaction, and operational performance, focus more on hospital performance (Fosso Wamba & Mishra, 2017). The most convincing benefits of big data are the IT infrastructure and operational benefits. This enhances the effectiveness and efficiency of IT and also helps improve clinical operations (Wang et al., 2018).

H1: Use of big data has a significantly positive influence on hospital performance.

2.2 Data Quality and Big Data Use

Data quality refers to the hygiene or appropriateness of data to meet business needs. The 7 attributes (i.e., accuracy, completeness and validity, accuracy and accessibility) cover the content and structure of data in general and cover several mistakes that are most often associated with poor quality information: data input errors, misapplied company rules, duplicate records and missing or incorrect data values. However, faultless data is useless if experts cannot understand or access the data in a timely way (Liu et al., 2020). In addition, high fault-tolerance availability, geo-division, and data replication. However, this can lead to problems in data quality, such as consistency in many data centers. Data sets collected are noise-based, reliable, accurate, etc. The cost of transmitting and storing raw data required. There may be strict data quality requirements with specific methods and applications for data analysis. Consequently, data preprocessing techniques should be used to improve data quality in large data systems (El Alaoui et al., 2019).

H2: Data quality has a significantly positive influence on the use of big data.

2.1.2 Data Integration and Big Data Use

In the Big Data era, people are generated, processed, and analyzed to an unparalleled degree and data-driven social decision-making. Because the value of data is exploded when connected and fused with other data. Data integration differed from conventional data inclusion in many dimensions: the number of data sources for one single domain, including tens of thousands, has grown to be quite dynamic. Data Integration is different in several dimensions from conventional data integration: even in a single domain, the number has risen to tens of thousands, many of the data sources are highly dynamic, with large quantities of new data collected being made available constantly, their structure is highly heterogeneous with a wide variety even for substantially similar data (Gunasekaran et al., 2017).

H3: Data integration has a significantly positive influence on the use of big data.

2.1.3 Data governance and big data Use

Big data governance is part of a broader data governance system, aligning policy with multi-functional goals on the optimisation, privacy, and monetization of big data (Al-Badi et al., 2018). The role of data governance is performed by data stewards and custodians in ensuring the proper management of the data through a process and method system (Al-Badi et al., 2018). Health policy is competing for access to information on the health side, particularly the conditions under which information for research should be accessible when appropriate privacy and security protections are developed (Hamidi, 2019). There are models to establish data-sharing arrangements that promote the appropriate use and attention to ethical standards by information in a safe and secure environment (Riso et al., 2017).

H4: Data governance has a significantly positive influence on the use of big data.

2.1.4 Mediating Role of Use of Big Data with Data Quality and Hospital Performance

The enormous volume of produced and processed data from diverse application domains has gained enormous momentum in recent years. The assessment of big data quality was defined as necessary if data quality measures, including completeness and accuracy, were to be guaranteed (Taleb et al., 2018). The degree of fitness for data usage by data users or customers is commonly used to calculate the data quality and captures a broad outlook on how the inherent and use-value of big data can be achieved and used. Many studies show that organisations will profit from data if they can unlock data value. These advantages include increased performance, profitability, and competitive advantages (Wahyudi et al., 2018).

H5: Use of big data positively mediates the relation between data quality and hospital performance.

2.1.5 Mediating Role of Use of Big Data with Data Integration and Hospital Performance

In addition, the findings also suggest that the link between inter-functional integration and operating flexibility can be fully mediated by hospital integration. Integration of hospital patients is recognized as essential to increased productivity of hospitals and patient care. Accurate, timely, and appropriate communication and interchange of information (e.g. patient health and medical information, medical records, lab results, prescriptions, and health insurance claims/transactions) between the hospital and its patients (e.g., healthcare service providers such as doctors, nurses and hospital staff) (Yu et al., 2021).

H6: Use of big data positively mediates the relation between data integration and hospital performance.

2.1.6 Mediating Role of Use of Big Data with Data Governance and Hospital Performance

As the commercial or public sectors recognize the needs of the consumer market, big data can be used to optimize their product or service for customer satisfaction. Yet, public health is the government's priority. In order for other patients to undertake treatment from the database, a health organization may share the same clinical record. Governance committees develop appropriate policies and promote the exchange of data across governmental and commercial sectors to minimize healthcare costs so they can work together to improve the quality of healthcare (Tse et al., 2018).

H7: Use of big data positively mediates the relation between data governance and hospital performance.

2.2 Underpinning Theory & Model

The theory underneath this study is the theory of the RBV. In this study, the impact of big data on Malaysian government hospital performance is being applied in the Delone & McLean IS Success Model (D&M ISSM). A research framework was established based on RBV Theory and D&M ISSM Model. The theory argues that organizations could achieve considerable increases in performance if IT resources match additional organizational aspects.

2.2.1 Resource-based view (RBV) theory

One of the well-recognized theories of business efficiency is the RBV theory. The RBV is focused on prior studies, which stressed the value of resources for improving business efficiency (Andersén, 2021). RBV stresses the influence of internal resources on the strategies and success of organizations. (Ghasemaghaei et al., 2018). The RBV claims that an organization should use a bundle of important intangible and tangible resources to achieve its competitive advantage. The inter-relationships between RBV, organizational innovation, and efficiency, building on earlier work in the RBV (Gupta & George, 2016). IT is focused on the capability of the company to combine or co-present IT-based resources with other resources and capacity. IT efficiency studies have generally used the strategically controlled RBV. Nevertheless, the idea of IT skills is based on the premise that a distinctive collection of skills mobilized by an organization cannot be disclosed easily and contributes to sustainable competitive advantages, whereas resources can be easily replicated (Chatzoglou et al., 2018; Sheikh et al.,2018). In the RBV, the ability to use big data can also be seen as one of the strengths of an organization, as this is a representation of an organisation's strategic purpose. (Yu et al., 2018). On the basis of RBV, the data analysis offers organizations strengths, but elements of other organizations (e.g., data, employees) are still important for data analytics to be fully used. The successful combination of resources between organizations, in particular, will improve decision-making efficiency, helping businesses to provide better services based on a thorough knowledge of their customers, markets, and the environment, resulting in a competitive advantage that is sustainable (Ghasemaghaei et al., 2018; Alta & Shahzad, 2018). In previous empirical studies the notion that IT is capable of showing its direct or indirect effect on performance results was employed. The key assumption in these studies is that a company must have invested in all the required resources in order to build a robust IT capability (Mikalef et al., 2018).

2.2.2 Model of DeLone and McLean model (D&M)

The DeLone and Mclean Success IS Model has attracted considerable attention by researchers in the field of information systems (Abrego Almazán et al., 2017). The D&M ISSM comprises six dimensions: quality of systems, information quality, information usage, user satisfaction, impact on individuals, and organizational impact. (Alkraiji, 2021). The D&M model evidently can be used to evaluate the success of the Information Systems in hospitals. The D&M model has been conducted, with few validating the model explicitly in a developing country in the context of hospital information systems. A study carried out in government hospitals in Korea was also based on a D&M model and evaluated the performance of newly designed information systems (Ojo, 2017). Researchers evaluated user satisfaction with the DeLone and McLean model approach in the hospital information system. The D&M model approach was applied for user's satisfaction with the use of the healthcare system in Sidenreng Rappang Regency Nene

Mallomo Hospital (Muin et al., 2020). Therefore, the present study highlighted the impact of use of big data in Malaysian government hospitals. Thus, Figure. 1 has shown the research framework of the present study and hypothesis.

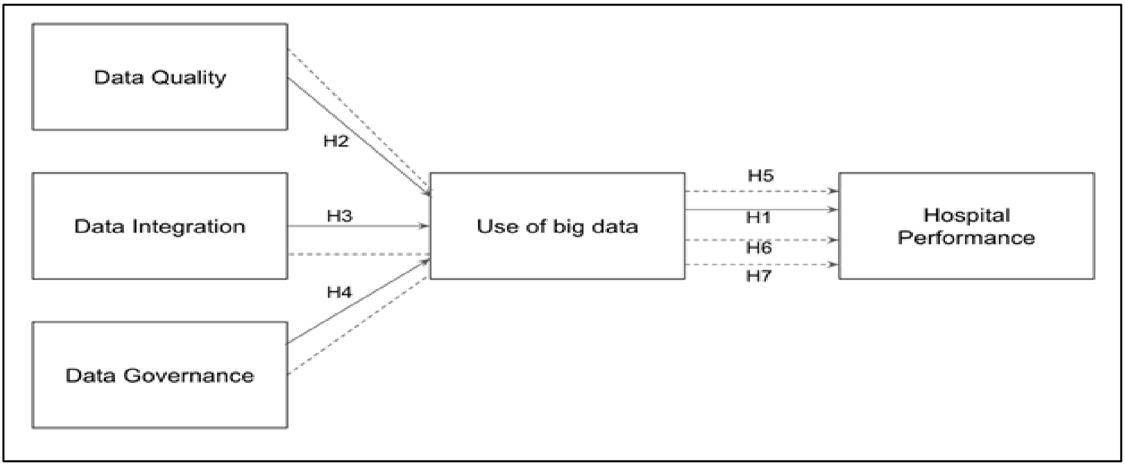

Figure 1: The Research Framework

3. METHODOLOGY

3.1 Instrument development

The current study developed an investigative tool based on previous research. The questionnaire has been big data adopted/adjusted, and re-written. All items have used a 5-point scale from 1 to 5, ranging from "strong disagreement" to "strong agreement." Use of big data, healthcare performance, data quality, data integration, data governance were taken from the questionnaires (Ahmed et al., 2018; Mikalef et al., 2018; Shamim et al., 2019; Wamba et al., 2017). The successful questionnaire tools for the impact of big data were adopted based on previous researchers (Ahmed et al., 2018; Mikalef et al., 2018; Shamim et al., 2019; Wamba et al., 2017). A 5-point range of Likert items from 1—"Poor," 2—"Fair," 3—"Satisfactory," 4—"Very good" to 5—"Excellent" were used for all successes to the impact of big data.

3.2 Data Collection

Convenience sampling facilitates the collection of information from those who can furnish it conveniently. In addition, subjects are chosen for the most accessible members. Convenience sampling is a less reliable solution, but it's an essential tool where fast and quick information is not easily accessible in situations of the population (Sekaran & Bougie, 2019). This is the best sampling approach for the present state of COVID-19. Geographical clusters (14 states of Malaysia) were formed for the control of reliability. Apply the Krejcie and Morgan minimum sample size in every 14 states (Refer to Table.

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1). The setting of data collecting has been drastically changed by COVID-19. While government directives for MCOs and physical isolation may have produced a global "standstill" for some, researchers have discovered that these measures have dynamic and profound consequences on the research process. With the contextual change in the gathering of data in mind, there are considerable threats. The study as the data collection tool was therefore forced to change from the traditional medium face-to-face to the fully online medium. The researchers collected data for this analysis in Google form distributed with a cover letter explaining the study's intent to the medical practitioners, senior administrators, and technical experts of the selected government hospitals in Malaysia. The cover letter is primarily attached to the questionnaires to remind each respondent that this questionnaire is regarded as confidential and used only for academic purposes. Data collected for this study from Malaysian government hospitals were used by all the states, including East Malaysia (Sabah and Sarawak). In addition, a number of messages (LinkedIn & WhatsApp), phone calls, and email reminders have been sent to the medical practitioner, senior administration, and technical experts of government hospitals, and a few questionnaires were obtained offsite during a conference call with the government hospital senior staff. The 560 questionnaires were distributed, only 212 (38 percent) returned the questionnaires (Refer to Table.2). Questionnaires were collected and circulated for five months between October 2020 and February 2021.

3.3 Data Analysis

However, in the current analysis, only the 212 questionnaires were used in their completion and satisfactory completion. Thus, the data seems more stable and accurate in the course of multiple studies by following this approach. The descriptive statistics referred to the minimum, maximum, mean, and standard deviations calculated on the five-point Likert scale used in the study questionnaire, from 1 to 5. The statistical results of the descriptive analysis were low to high as were ranging from 2.88-3.78, the standard deviation scores ranged from 0.70 to 0.87. The profile of the respondents is listed in Table. 3. Demographic analysis reveals that most respondents are aged 18-30 (43.9 percent), aged 31-40 (41.5 percent), approximately 12.7 percent between 41 and 50 years, approximately 1.9 percent between 51-60 years, respectively. The distribution of the respondents is dependent on age.

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Table1: Sampling with Proportional Technique

State	No. of hospitals	Total Hospitals	Sample	Krejcie & Morgan (1970)	Krejcie & Morgan Required sample from each cluster	Required sample size	Required sample from each cluster	Total Respond	Actual response received	Actual Respond percentage
Johor	12	144	8.33%	106	9	200	17	212	13	6.13%
Kedah	9	144	6.25%	106	7	200	13	212	29	13.68%
Kelantan	10	144	6.94%	106	7	200	14	212	3	1.42%
Kuala Lumpur	6	144	4.17%	106	4	200	8	212	24	11.32%
Labuan	2	144	1.39%	106	1	200	3	212	0	0.00%
Malacca	3	144	2.08%	106	2	200	4	212	6	2.83%
Negeri Sembilan	7	144	4.86%	106	5	200	10	212	23	10.85%
Pahang	11	144	7.64%	106	8	200	15	212	14	6.60%
Penang	6	144	4.17%	106	4	200	8	212	15	7.08%
Perak	15	144	10.42%	106	11	200	21	212	12	5.66%
Perlis	1	144	0.69%	106	1	200	1	212	0	0.00%
Putrajaya	2	144	1.39%	106	1	200	3	212	9	4.25%
Sabah	20	144	13.89%	106	15	200	28	212	13	6.13%
Sarawak	23	144	15.97%	106	17	200	32	212	11	5.19%
Selangor	11	144	7.64%	106	8	200	15	212	37	17.45%
Terengganu	6	144	4.17%	106	4	200	8	212	3	1.42%
	144				106		200		212	

Table 2: Response Rate of the Questionnaires

Response	Frequency & Rate
Number of Questionnaires	560
Questionnaire Returned	212
Return and Usable Questionnaire	212
Return and Excluded Questionnaire	0
Questionnaires not Returned	348
Response Rate	38%
Valid Response Rate	38%

Table 3: Demographic Profile of Respondents

Demography	Description	No. of Responses	% Age			No. of Responses	% Age
Gender	Male	72	34.0	Represent State	Selangor	37	17.5
	Female	140	66.0		Kuala Lumpur	24	11.3
Age	18 to 30 years	93	43.9		Kedah	29	13.7
	31 to 40 years	88	41.5		Negeri Sembilan	23	10.9
	41 to 50 years	27	12.7		Pahang	14	6.6
	51 to 60 years	4	1.9		Sarawak	11	5.2
Hospital Experience	1-10 years	165	77.8		Penang	15	7.0
	11-20 years	42	19.8		Putrajaya	9	4.3
	21-30 years	5	2.4		Perak	12	5.7
Job Position	Senior Administration	15	7.1		Johor	13	6.1
	Medical Practitioner	64	30.2		Malacca	6	2.8
	Technical Expert	133	62.7		Sabah	13	6.1
Qualification	Certificate/ diploma	51	24.1		Kelantan	3	1.4
	Bachelor's Degree	113	53.3		Terengganu	3	1.4
	Postgraduate or Higher Degree	48	22.6				

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In comparison, the female respondents have a higher response rate of 66% compared to 34% of male respondents. The male holds the dominant position in Malaysian culture, especially in the healthcare sector. In addition, 53.3%% of the responses were obtained from participants who graduated with a bachelor's degree, another 22.6% have a postgraduate degree, and the remaining 24.1% have a college certificate and Diploma holders only. On the other hand, the senior administration answered 7.1% of the questionnaires, and only 30.2% and 62.7% were healthcare practitioners and technical experts.

3.4 Data Analysis Using SmartPLS

The study utilized SmartPLS 3.3.2 to facilitate data analysis to achieve the research objectives. In several disciplines, based on inferential analyzes, the application of Partial Least Squares-Structural Equation Modeling was used in various areas (Hair et al., 2020). These developments contribute to the growth of PLS-SEM, which is generally used as a research tool in information and social science management systems. Further, confirm that PLS can analyze variables simultaneously in complex models. In SmartPLS, two main measures and structural models are evaluated (Shahzad et al., 2021). The first step is the evaluation of a model measurement, and the second step, a measure of a structural model (As shown in Table. 4), as the current research, adopts two stages (Hair et al., 2019, 2020).

Table 4: A Two-Step Process of PLS Path Model Assessment

STEP 01	Assessment of measurement model	• Ascertaining internal consistency reliability • Ascertaining convergent reliability • Ascertaining discriminant reliability
STEP 02	Assessment of structural model	• Assessment the significance and relevance of structural model relationships • Assessment the level of $R2$ • Assessment the effect size $f2$ • Assessment of predictive relevance $Q2$ • Examining the mediating effect

Source: Hair et al., 2020

3.4.1 Internal Consistency Reliability

Internal reliability refers to "the measurements made of the same term by any object on any specific subscale" (Hair et al., 2020). Initially, there must be a minimum composite reliability cutoff value of 0.70, and the AVE is more than 0.50 (Hair et al., 2019, 2020). Reliability values of between 0.60 and 0.70 are considered 'acceptable' values in exploratory research. Reliability values between 0.70 and 0.90 range from "satisfactory

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Table: 5 Indicator Loadings, Internal Consistency Reliability, and Convergent Validity

Construct	Item	Loadings	Composite Reliability	Average Variance extracted	Construct	Item	Loadings	Composite Reliability	Average Variance extracted
Data Governance	DG1	0.887	0.959	0.823	Hospital Performance	HP1	0.559	0.880	0.600
	DG2	0.893				HP2	0.806		
	DG3	0.920				HP3	0.852		
	DG4	0.917				HP4	0.795		
	DG5	0.919				HP5	0.826		
Data Integration	DI1	0.838	0.930	0.728	Use of Big Data	UBD1	0.811	0.930	0.654
	DI2	0.865				UBD2	0.813		
	DI3	0.852				UBD3	0.784		
	DI4	0.839				UBD4	0.838		
	DI5	0.872				UBD5	0.805		
Data Quality	DQ1	0.775	0.924	0.708		UBD6	0.768		
	DQ2	0.849				UBD7	0.839		
	DQ3	0.863							
	DQ4	0.880							
	DQ5	0.835							

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to good." Values of 0.95 and above are problematic because they show that the elements are redundant, decreasing the validity of the structure (Hair et al., 2019). Both variables in the current study have AVE and composite reliability as defined in Table. 5, an indicator of calculated model reliability, which is above the threshold value of 0.5. Table. 5 describes the acceptable range of the average variance extracted (AVE) and composite reliability values for all variables. The high reliability of all variables and AVE values surpasses limits, demonstrating that the measurement model is accurate.

3.4.2 Discriminant Validity

The discriminatory validity criterion measures how much a variable is not equivalent to other constructs (Shahzad et al., 2021). The present research explored discriminatory validity through the use of AVE (Franke & Sarstedt, 2019). The correlation between latent constructions and the square root of AVE, as indicated by Fornell and Larcker in 1981, as it was obtained by comparing discriminatory validity. In addition, They proposed that an average variance with a score of 0.50 or higher be used to test the discriminatory validity (Shahzad et al., 2021). This study considers discriminatory validity to validate the external consistency of the model to examine the discriminating validity. However, as described in Table. 6, the comparison between latent constructions revives the square root of AVE of the construction: Data Governance (DG)=0.907; Data Integration (DI)= 0.853; Data Quality (DQ)= 0.841; Hospital Performance (HP)=0.775; and use of Big Data (UBD)= 0.809. Furthermore, A strict HTMT criterion for determining discriminant validity in variance-based SEM. HTML value should be no value of 0 between the 90 percent bootstrap confidence interval of HTMT to prevent discriminant validity (Hair et al., 2019). As shown in Table.7, all of the values met the HTMT 0.90 requirements (Franke & Sarstedt, 2019). This meant discriminant validity had been established.

3.4.3 Assessment of Measurement Invariance

The model's evaluation considered that the measurement model confirms the reliability and validity of the model. The external load must be 0.50 and higher in accordance with the thumb law. It must be over 0.50 for the average variation extracted. However, this technique is recommended for a factor loading below 0.50 which starts from the lowest value because it improves overall data quality (Hair et al., 2019, 2020). Figure. 2 shows the acceptable range of the average variance extracted (AVE) and composite reliability values for all variables that proved the measurement model's reliability.

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Table 6: Discriminant Validity Matrix

	Data Governance	Data Integration	Data Quality	Hospital Performance	Use Big Data
Data Governance	0.907				
Data Integration	0.626	0.853			
Data Quality	0.641	0.591	0.841		
Hospitals Performance	0.521	0.565	0.549	0.775	
Use of Big Data	0.451	0.482	0.612	0.432	0.809

Table 7: HTMT

	Data Governance	Data Integration	Data Quality	Hospital Performance	Use of Big Data
Data Governance					
Data Integration	0.675				
Data Quality	0.704	0.655			
Hospital Performance	0.592	0.651	0.639		
Use of Big Data	0.476	0.507	0.659	0.479	

3.4.4 Assessment of Significance of the Structural Model Direct Relationships

The importance of relationships is investigated in places where beta values are the coefficient of regression and t-values. T- value larger than 1.64, which is used further in the proposed hypothesis's decision-making process, is considered important (Shahzad et al., 2021). In this analysis, four direct relationships were investigated using a structural model, with significance levels and t-values calculated using the SmartPLS 3.3.2 bootstrapping function. As a result, the confidence interval was constructed using 5000 bootstrap subsamples, which was more than the 212 valid observations. The results were generated with the help of SmartPLS 3.3.2 and illustrated the path p-value, t-value, coefficient value, and standard errors as shown in Figure. 3. According to the results of these values, the hypotheses decisions were made and their significance levels.

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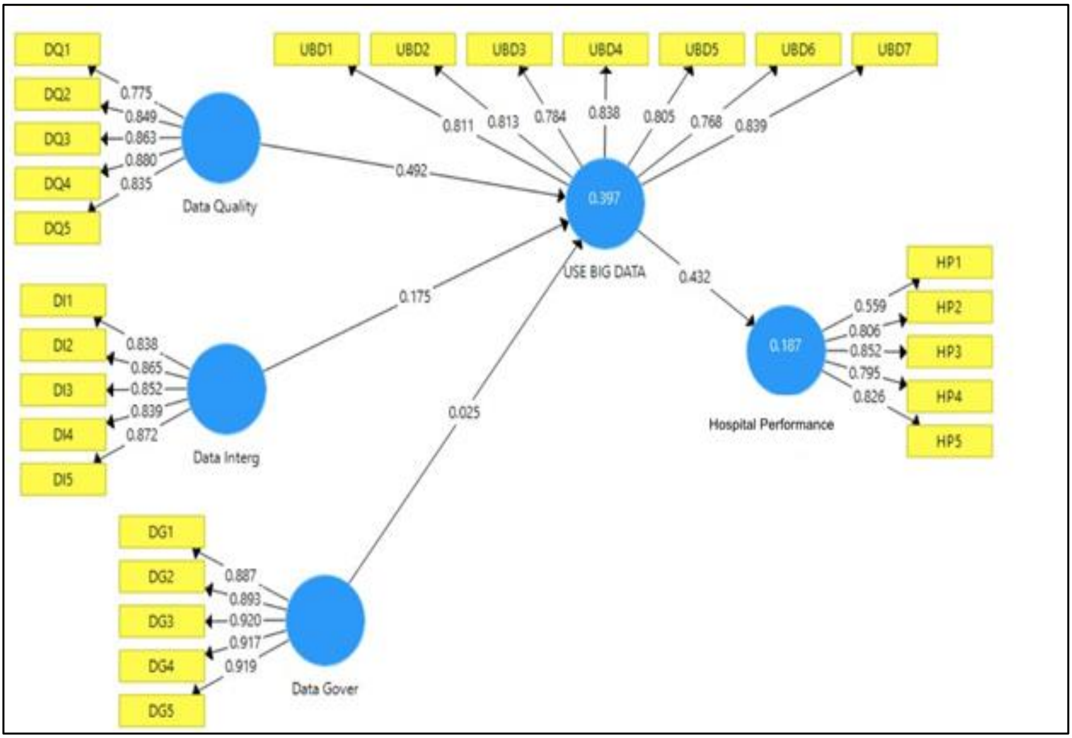

Figure 2: PLS Algorithm Measurement Model

First, this analysis aims to concentrate on model evaluation with direct links and, secondly, to investigate the relationships hypothesised by the internal model between variables.

However, out of four (4) hypotheses, three (3) hypotheses have demonstrated their support, and only one (1) has been considered not supported based on the t-value recommended. However, the direct effect on firm output (dependent variable) of any latent structure can be seen in Figure. 3. According to the researchers, data integration (DI) had an at-value of 2.159, data quality (DQ) had an at-value of 5.424, use of big data (UBD) had an at-value of 8.202. These indicated meditation and significance except data governance (DG) with a t-value of 0.257 that result is insignificant and weak after including Use of big data as a mediator with hospital performance.

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Table 8: Hypothesis Testing (Inner Modeling Analysis)

NO	Hypothese Path	Path coefficient	Standard Error	T Value	P Value	Decision	0.05%	0.95%	F-size	VIF	R Square	R Square Value	Q2
H1	UBD-> HP	0.432	0.053	8.202	0.000	Supported	0.333	0.509	0.230	1.000	HP	0.187	0.101
H2	DQ -> UBD	0.492	0.091	5.427	0.000	Supported	0.329	0.629	0.213	1.886	UBD	0.397	0.249
H3	DI -> UBD	0.175	0.081	1.980	0.015	Supported	0.037	0.303	0.028	1.828			
H4	DG -> UBD	0.025	0.099	0.250	0.399	Not Supported	-0.134	0.192	0.001	2.020			

Note: Use of Big Data (UBD), Hospital Performance (HP), Data Quality (DQ), Data Integration (DI), Data Governance (DG).

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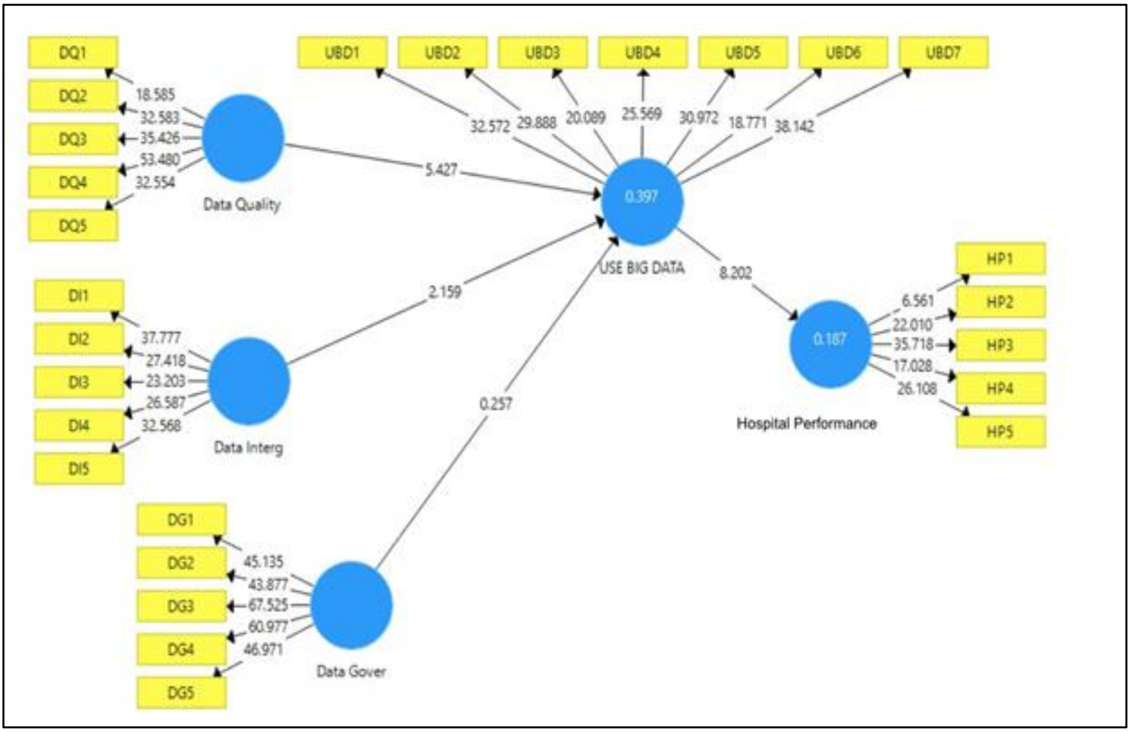

Figure 3: Structural Model Direct Relationships

4. DISCUSSION

4.1 Results Comparison

Hair et al. (2019) described appropriate R2 values as 0.75 for significant predictive accuracy, 0.50 for moderate predictive accuracy, and 0.25 for poor predictive accuracy. The R2 values as endogenous variables HP and UOB have a modest degree of predictive accuracy, as shown in Table. 8. DG and UOB variables have a low degree of predictive accuracy, as stressed by (Hair et al., 2017). While In 1988, Cohen suggests that a 0.35 value of f2 indicates a large effect size, a 0.15 value of f2 indicates a medium effect size, and a 0.02 value of f2 indicates a small effect size (Hashmi et al., 2021). The F2 values are shown in Table. 8, and it can be shown that data integration (0.028) has smaller effect sizes in producing R2 of UBD. Furthermore, data quality (0.213) has a medium effect size in determining the R2 of UBD. UBD (0.230) has a substantial effect size in producing R2 of HP.

Using Stone and Geisser's method Q2, the predictive relevance (Q2) has been investigated for evaluating the route model's predictive accuracy (Chin et al., 2020). To determine the value of Q2, the blindfolding technique was used in the reflective

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measurement model using SmartPLS 3.3.2 (Shmueli et al., 2019). Table.8 shows the Q2 values of endogenous constructs, and it can be shown that all of the HP (Q2 =0.101) and UBD (Q2 =0.249) values are greater than zero, indicating that the current study's model has ample predictive relevance. Furthermore, for evaluating the mediation effect, bootstrapping was used to obtain the t-values and confidence intervals. Therefore, the result of the bootstrapping analysis (see Table. 9) indicated the t-value of 4.372 to be significant in terms of the indirect effect path coefficient 0.213. Indirect confidence interval Bias-correct: The link between LL=0.134, UL=0.289) and Data Quality (DQ) indicates that Use of Big Data (UBD) and Hospital Performance (HP) relationship, which supported H5 of the present study, were not straddled 0 between.

Table: 9 Test of Mediation (Indirect Effect*)*

NO	Hypothesized Path	Path Coefficient	Standard Error	T Value	P Value	0.025	97.50%	Decision
H5	DQ -> UBD-> HP	0.213	0.049	4.372	0.000	0.134	0.289	Mediation
H6	DI -> UBD -> HP	0.076	0.038	1.980	0.024	0.015	0.141	Mediation
H7	DG -> UBD -> HP	0.011	0.044	0.250	0.401	-0.058	0.086	No-mediation

Note: Use of Big Data (UBD), Hospital Performance (HP), Data Quality (DQ), Data Integration (DI), Data Governance (DG).

The result of the bootstrapping analysis (see Table. 7) indicated the t-value of 1.980 to be significant in terms of the indirect effect path coefficient 0.076. Indirect confidence interval Bias-correct: The link between LL=0.015, UL=0.141) and Data Integration (DI) indicates that Use of Big Data (UBD) and Hospital Performance (OP) relationship, which supported H6 of the present study, were not straddled 0 between. The t-value of 0.250 to be insignificant in terms of the indirect effect path coefficient 0.011 (see Table. 7). Indirect confidence interval Bias-incorrect: The link between LL=-0.058, UL=0.086) and Data Governance (DG) indicates that Use of Big Data (UBD) and Hospital Performance (HP) relationship, which supported H7 of the present study, were straddled 0 between.

5. THEORETICAL IMPLICATION

The study provides several theoretical contributions by using convergent parallel design and developed a research framework based on the RBV theory and D&M ISSM model to assess the use of big data. Research in use of big data generally and big data in the healthcare industry in Malaysia may be considered unique in terms of academic implications. The first significant impact of this research in big data is that D&M ISSM are validated in the context of big data adoption and that the two are expanded to increase their ability to show this adoption. In this study, the factors that affect big data use through the extension of D&M ISSM have been proposed and examined to include factors more related to hospital performance in Malaysian government hospitals. RBV discusses the tangible and immaterial factors that contribute to better performance for government hospitals. This study helps researchers understand in-depth the relationship between DQ, DI, and DG and their connections to the healthcare sector's performance, using big data as a mediating variable between UBD. It, therefore, confirms, based on all these present study variables, that the use of big data depends on the perceptions of healthcare practitioners, administrators, and technical experts on their effectiveness. In addition, this study is the first to empirically validate the relationship between big data utilization and the healthcare sector in Malaysian government hospital performance. The study empirically developed, tested, validated the model, and again provides a valid model for other researchers to investigate the impacts in types of hospitals (Government or private) or other countries of use of big data in hospital performance. Furthermore, a review of recent literature on technology use and hospital performance suggests that most research has been carried out by developed countries such as the United States, Europe, and Latin America, in contrast ignoring countries such as Asian Pacific countries like Malaysia as well as African countries. In particular, by conducting this study in Malaysia, It is expected to improve the understanding of the Malaysian government hospitals performance and other developing countries in the whole of the healthcare industry (Ahmed et al., 2017).

6. PRACTICAL IMPLICATION

Government and policymaker must recognize that their big data decisions have a direct impact on government hospital activities. But it must disclose what the government and policymakers can do to improve Malaysian government hospital performance and sustainability. The study showed that the healthcare sector lacks big data-related activities and that the main cause of government hospitals performance is its operations in an unsatisfactory delivery to the public. Our results provide practical feedback and guidance to health professionals engaged in big data analysis. First and foremost, the decision support for the creation of meaningful clinical reports is one of the critical capabilities of big data analytics. Based on the results of this study and on several previous studies, big data based on RBV theory and the D&M SSM framework has been established empirically. Thus, senior administrators, healthcare practitioners, and technical experts must recognize the importance of big data as a mediator with all positive relationships, based on RBV theory, in indirectly enhancing government hospitals performance. It is implied that the use of big data increases and ultimately improves government hospitals performance or competitiveness with the private sector when it becomes more technology-oriented.

7. CONCLUSION

The primary aim of this study is to investigate the mediating role of big data use and the direct relationship between the independent and dependent variables. The current study found that by measuring four direct relationships with firm results, three (3) of the four (4) hypotheses of the first objective were met (DV). The research shows that DI, DQ, and UBD have a significant relationship with firm efficiency (HP). Based on the results, Five out of seven hypotheses be significant. The relationship was intended to assess the strength and validity of hospitals performance of the mediating variable. The research provides empirical evidence that UBD, hospital performance is significantly related (HP). The findings demonstrate the mediation between DQ, DI, DG, and Hospital performance using big data (UBD). Future research can also explore how and why big data contributes to improving some IT-enabled transformation activities through thorough single or multiple case studies. Furthermore, the study makes practical, theoretical, and methodological contributions to understanding the impact of these DMISSM factors on the output of the healthcare industry. This study has useful consequences in the success of government hospitals and big data literature, both technically, theoretically, and methodologically.

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