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Assessing the Big Data Adoption Readiness Role in Healthcare between Technology Impact Factors and Intention to Adopt Big Data

Ebrahim A. A. Ghaleb [1,*], P. D. D. Dominic [1], Narinderjit Singh Sawaran Singh [2] and Gehad Mohammed Ahmed Naji [3]

1 Department of Computer and Information Sciences, Universiti Teknologi PETRONAS, Seri Iskandar 32160, Malaysia; dhanapal_d@utp.edu.my
2 Faculty of Data Science and Information Technology, INTI International University, Nilai 71800, Malaysia; narinderjits.sawaran@newinti.edu.my
3 Department of Management & Humanities, Universiti Teknologi PETRONAS (UTP), Seri Iskandar 32610, Malaysia
* Correspondence: ebrahimghaleb85@gmail.com

Abstract: Big data is quickly becoming a new area where administrative work can be improved. Even so, it is still in the early stages of being used in hospitals in countries with less technology. Therefore, there is an inadequate grasp of the evaluation of big data adoption preparedness in the healthcare sector as data-point-determined insights become crucially useful in healthcare institutions in underdeveloped nations. This process, called "digital transformation," has a lot of benefits; for example, it helps healthcare organizations to create more efficient processes, offer different services, give better care, make more money, and cut costs. This paper aims to suggest and assess a conceptual framework that focuses on technological factors and can assist in determining the readiness of healthcare institutions in developing nations to utilize big data. Although the study can offer valuable perspectives on the advantages that can arise from adopting big data in the healthcare sector, it is important to highlight that leveraging big data analytics in healthcare has the potential to enhance the efficiency and effectiveness of healthcare services. This, in turn, can indirectly contribute to sustainability objectives by optimizing the allocation of resources, minimizing waste, and improving patient outcomes. A total of 328 healthcare workers from Malaysia were subjected to experimental testing of the model. The collected data were evaluated using the Smart PLS 3 program and the structural equation model (SEM). The study's findings supported our hypotheses. The results showed that technological factors affected the participants' perception of their readiness for big data, which ultimately influenced their interest in utilizing it. By concentrating on big data preparedness in the healthcare industry and ambition to utilize big data, this research provides an important theoretical contribution. Employees who are "big data ready" would benefit from the study's results, as, through their recognition, said employees are more likely to increase the desire to use big data in Malaysia's healthcare sectors.

Keywords: technology factors; big date adoption (BDA); technology readiness; healthcare; public health; psychological wellbeing

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1. Introduction

Organizational reinvention using digital technologies to enhance performance and accomplish organizational objectives is known as "digital transformation." Given the urgency of the global transition to digital healthcare, healthcare transformation is seen as essential. The benefits and drawbacks of digitization and transformation for contemporary healthcare companies are many. There have been several in-depth considerations and analyses of healthcare digitalization, such as the study conducted by [1]. To construct and enhance the future of care delivery and establish a patient-centered, evidence-based framework where value is rewarded over volume, a wide variety of stakeholders have developed a unified vision for healthcare reform. The fundamental technological advancements that are driving this shift are freshly created and advancing quickly [2]. Smartphones, sensor-based technologies, digital health apps, and big data (BD) are all part of this digital transformation. The healthcare sector is expanding at a faster rate, which is why there are more sources of healthcare data. Processing more data at once makes it challenging to prevent data loss. Big data may be used to address data processing problems and do additional analytics on data, which can be utilized for many different things. Additionally, it enables us to obtain pertinent data from the data warehouse and utilize it to properly prescribe medication and provide timely care [3].

The phrase "big data," which is used to characterize this enormous collection of information, has been rising dramatically in recent years, which creates both unparalleled potentials for insight and development and unprecedented obstacles. As a result, it is thought that artificial intelligence (AI), which is defined as a field of computer science that focuses on the production of intelligent robots that function and respond like people, is presents the best course of action by which to address some of the BD difficulties in healthcare. Initial applications of AI in healthcare have traditionally concentrated on certain diseases or small groups of patients, but since the industry leans more and more upon it to analyze and utilize data from vast patient populations, its potential future uses are limitless [4].

According to [5,6], the term "BD technologies" refers to datasets that are too big for conventional data-processing tools to handle and need to be processed by new technologies. In line with this basic description, the term BD can be further defined as a collection of data that goes above and beyond the capabilities of standard database management software used in the healthcare industry. There is an urgent need for more current and powerful software that can process, analyze, and handle the enormous quantity of information and data that has been gathered and saved because this traditional software is unable to do so.

According to Petersen [7], digital technology has the potential to alter industries, including the economy, healthcare, and medicine. Emerging technologies can securely store medical records and keep a copy of the original. Most healthcare providers, including physicians, hospitals, laboratories, and insurers, might request authorization to access patient records using developing technology. Patients who have access to their data have greater power, and doctors may treat patients more effectively because of more reliable and readily available data. These data include proof of the acts or transactions of the organization.

2. Related Work

With the effect of BD on policies related to corporate governance and strategic management on the one side, the separation of administrative roles is another field of focus. Management necessitates sophisticated and cognitive abilities [8]; hence, on the subject of the first factor, the challenges raised by BD usage necessitate more research aimed at defining the cognitive and complex competencies that management needs to learn in order to effectively face these challenges [8]. Second, it is crucial to consider how the organization's articulation of management responsibilities is affected by the proliferation of data and the deployment of BD analysis (see, for instance, [9]). The most successful organizational learning models that provide enough transparency at any level of the company with respect to the strategy implementation process were examined, as were the prerequisites for effective interaction between the chief data agents and the chief marketing agents [10].

According to [11], BD is a set of frameworks and cutting-edge technologies that have been designed to extract knowledge and vital information from large volumes of data in diverse forms, culminating in data processing and high-speed data acquisition. The authors of [12] came up with a rate based on the number of items on the list, made a structure, and made a distinction between data store, access, convergence, traditional, and BD. From 2005 to 2020, data volume will increase from 130 exabytes to 40,000 exabytes [11]. Techniques for the volume factor of BD are suggested, showing how the data are time-calculated, in line with the prediction made by the International Data Corporation (IDC) [13]. It uses BD volume. It also encouraged the departure from the norm to save time [13]. The push for BD analysis in healthcare and the increasing significance of cloud services have changed how healthcare is seen [14]. The cloud is quickly obtaining health data, medical practitioners are exchanging information, and BD medical library analytics are expanding.

The volume increase requires the inclusion of external data-gathering facilities, storage structures, a contemporary environment, and technology capable of accommodating massive datasets [12]. Because BD applications need a lot of data, storage is an issue that needs to be thought about as early as possible in the design process. Standard storage systems would continue to be incapable of accommodating massive quantities of data [15]. For BD analytics to work, you need a modern method, the right skills, and the ability to capture, process, and understand data using BD-related data-processing techniques such as Hadoop, Spark, and others. More data management systems, storage structures, and innovative environments and technologies are needed to satisfy enormous data demands because of the rise in volume. This latest revolution necessitates effective processes to turn big data into usable intelligence [15]. BD has shown itself to be one of the most significant investments for a business, enabling it to discover new concepts and acquire a greater understanding of hidden values. Given the rapid pace of change in the current world, BD has a significant impact on an organization's core components. Before embarking on the BD path, it is necessary to recognize and tackle a new critical issue that big technology's new features and needs have spawned: it is essential to remember that when data quantities increase, the available technologies, procedures, analysis, and management approaches might change [16].

2.1. Healthcare in Developing Countries

Healthcare aims to maintain and improve human wellbeing by detecting, aiding recovery from, and preventing disease. It generates immense amounts of data every day, inspired by clinical care, auditing, administration, and mandates to conform with recommendations and requirements. BD will fund several medical and welfare projects, including support for clinical decision-making, epidemic control, and population health management [17]. BD analyzes the transition of data and strategies from hierarchical, semi-structured, and unstructured data collection and terminal settings to a pervasive cloud-based environment. BD analyses and medicine apps make use of exponentially growing data volumes to discover similarities, trends, and difficulties of data complexity, as well as practical lessons for improved decision-making. They also present the possibility of improving results, thus lowering rising healthcare costs. To take advantage of this potential, health organizations must invest in insufficient services, facilities, and methods [17,18].

A large-scale, integrated system known as a health information system (HIS) was created to store, modify, and retrieve administrative and clinical information. It provides essential data to each management level at the appropriate time, place, suitable form, and location [19]. Then, effective decisions are made based on this information. Thus, healthcare plays an important role in making plans, managing, organizing, and controlling how the hospital sub-systems operate [20,21]. It also provides details on the synergistic organization. Healthcare will improve the quality of patient care through the evaluation of data, suggesting better care and encouraging hospitals to examine care quality and appropriateness concurrently rather than retrospectively.

In healthcare, IS is concerned with how information is processed and how doctors communicate and engage in medical tasks and practices in addition to education and research, such as information science and technology [22]. In healthcare organizations, such as hospitals, IS has been labeled differently, including electronic health records, HIS, and health record systems [23].

In developing countries such as Malaysia, the goals of HIS include supporting healthcare services, administration through electronic data processing, improving healthcare quality, lowering costs, efficient delivery of high-quality health services, and supporting knowledge-based systems that provide patients with the good analytical provision and interference for patient care activities [24,25]. Because it offers so many benefits, information technology is increasingly being used in the healthcare sector. The purpose of this research is to look at the IT profiles of small, middle, and enterprise (SME) private healthcare businesses in Malaysia, as well as the attitudes of their staff members toward the usage of HIS at work. The benefits of information technology are quickly being used in the healthcare industry. IT enables healthcare organizations to raise the standard of their staff members' efficiency and output, while also improving the facilities and patient care that they provide [26,27].

Several studies have been carried out in Malaysia. For example, [24] carried out a qualitative study that focused on implementing healthcare and its user perspective. The research was based on information gathered from participant opinions, and perspectives on developing and implementing were shared by two hospitals. Another qualitative study by [24] aimed to examine users' level of satisfaction with using healthcare. It was found that users' levels of satisfaction with health sectors in Malaysia differed regarding the quality of healthcare functions, performance of HIS, HIS interface quality, and the quality of healthcare sectors, which is a combination of the three previous qualities. Thus, healthcare becomes problematic when users show reluctance and encounter difficulties in using it. Three analysts with training in qualitative analysis carried out the interviews with the help of two research assistants. Each interview lasted between 40 and 55 min, and all participants provided their consent for the session to be recorded. The hospital's director gave his approval to the report [27].

2.2. Challenges in Healthcare Implementation in Developing Countries

People in Malaysia are becoming more aware of how important information technology is to the delivery of public services such as healthcare. The government's implementation of innovative ICT policies and plans demonstrates this understanding. Recent healthcare research suggests transforming health management information systems into health information management systems to create a statewide comprehensive HIS that can overcome obstacles and satisfy future needs [28,29]. One of the programs pushed is the integration of IS into Malaysian public hospitals, as well as the development of ICT in Malaysia and the government's 2020 objective to convert Malaysia into a developed country. However, the implementation and adoption of HIS in Malaysia still face some obstacles, as identified by some previous studies reviewed in this sub-section [30].

According to Bakar [31], HIS technology and business HIS implementation in Malaysian public hospitals were investigated. Content analysis of interview data using NOVA showed that each type of HIS has various stages, but the actions are still the same. Moreover, the kinds of HIS investigated still encounter different challenging issues, especially concerning users' acceptance and satisfaction levels. The challenges identified are high costs; time consumption; technological and technical challenges, such as the complexity of systems and system integration; fundamental issues, including users' lack of computer skills, complicated or challenging tasks, and complicated functions; and finally, issues related to ethics, such as privacy, certification, and confidentiality.

Other previous studies have also identified several challenges faced by HIS, including a lack of budget related to IT, a lack of IT skills, a lack of effective leadership, users' resistance to change, a lack of good infrastructure, and disrupting the structure of the national economy. Other more difficult factors include a rapidly changing operating environment in which healthcare quality expectations are rising, no quality nursing is available, and aged healthcare services are meeting escalating demands, as well as a formal lack of social security, the fact that insurance products are underdeveloped, and the fact that savings are limited [32,33].

Ref. [34] stated that the capital cost needed to equip a hospital with a Total Health Information System (THIS) is estimated to range from 80 to 100 million Malaysian ringgit (MR). This significantly high investment suggests that if a project fails to achieve its aims, it will be a massive loss for the Malaysian government. If challenges are not appropriately addressed, especially while implementing HIS, such challenges will increase the possibility of HIS failure in the future. These challenges are knowledge, culture, data, skills, system quality, and data. Based on this study, it seems that HIS implementation has brought a new perspective to ICT applications. The complex design of the hospital organization compared with other organizations is also a more difficult problem for HIS implementation. Moreover, since hospitals are organizations dealing with human health and life, ICT application and implementation are vulnerable to challenging issues [35].

The value of data is increasing at an unprecedented rate in a variety of sectors around the world. As a result of this expansion, there is an immediate need to create a method that allows for data assimilation and analysis in order to make smarter decisions [36]. According to [37], there are various procedures for setting up records, including consolidation, separation, labeling, lookup, and access to both unstructured and organized data. Data could grow from a few hundred terabytes to many petabytes. The biggest problem is managing and analyzing large amounts of data in order to recognize important decision-making patterns [38,39]. In the past, BD analysis has mostly focused on technological aspects (such as machine learning or technical algorithms) and the creation of devices.

2.3. Theoretical framework and Development Hypothesis

In this study, the literature was evaluated to identify important findings from previous research and establish a basis for creating the research framework. The review of the existing literature revealed that the information technology innovation sector has been thoroughly explored and is among the most advanced in the industry. According to [40–43] extensive research has been conducted on the contextual factors that influence the adoption of BD. Furthermore, [43] suggests that technology adoption is complex and dependent on various technical, organizational, and environmental factors, which may differ across different innovations [44].

It is important to take into account the cultural and social backgrounds of users during the process of adopting innovation, as these factors could potentially impact the technology's future success or failure [45]. The economic and social structures of cloud computing vary significantly between developed and developing countries. Studies conducted previously have highlighted the crucial role of sociocultural elements and values in the adoption of technology across different community methods, regardless of the country's level of development [46].

Nowadays, mobile phones and smartphones are becoming more popular, so developing nations have greater access to modern technologies, which positively influences their social development [47]. Recent studies have also shown a correlation between smartphone use and economic growth [48]. From this perspective, previous research has shown that increasing smartphone use alone would not be sufficient to close the present technological gap in developing nations [49]. Emerging technology is notably distinct from existing technology because of its distribution mechanisms and virtualized nature. BD cannot be evaluated from the perspective of human connection, but it may be evaluated through technology such as computers and cell phones. Current BD research has a considerable focus on healthcare [50]. Using BD services, especially electronic health records, is a popular way for the healthcare industry to reap the benefits of modern technology without incurring the high-quality and administrative costs often associated with on-premises systems and capital investments [51].

The research model illustrated in Figure 1 examines the impacts of technology, organizational and environmental factors, the usability of new technologies, and healthcare planning on one another. It is expected that the technical background factors of compatibility, knowledge level, and device quality would significantly influence the dependent variable, BD acceptability, with the backing of senior management. It is hypothesized that the operational background variables of financial support and training will have a significant impact on the independent technological preparedness variable. Complexity and compatibility, governmental IT regulations, government policies, and laws that consider the surrounding environment were predicted to have a considerable influence on the adoption of BD. The impact of these elements on the acceptance of BD is to be assessed. The following set of hypotheses was generated by the analysis model.

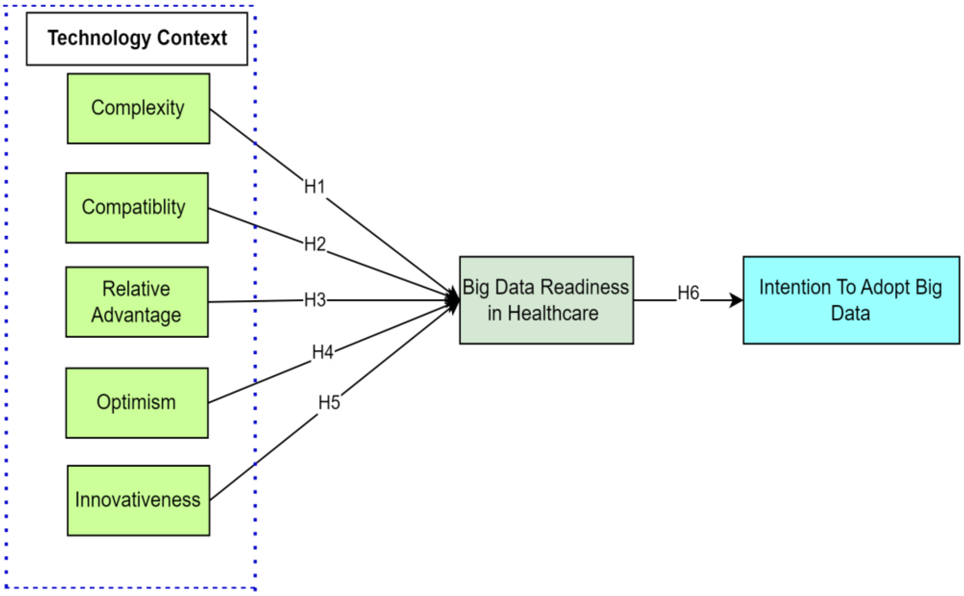

Figure 1. The proposed research model for BD adoption in healthcare.

To facilitate model validation via subsequent statistical analysis, a priori assumptions based on a positive, deterministic philosophical framework were developed. The ideas focus on the interaction between the dependent variables 2 and 3, which propose to apply BD, and the independent variable 1, which is the technical model.

2.3.1. Technology–Organization–Environment (TOE)

The TOE framework provides a unique perspective on IT adoption, considering the technological, organizational, and environmental contexts [52]. An extensive approach to examining creativity is to analyze contingency variables that impact firm decisions [53]. Infrastructure, TOE, and organizational effects are considerations that can be combined to justify results in organizations. The TOE system is useful for the structured study of innovation impact within an organization. According to Tornatzky [54], TOE helps to differentiate inherent creativity characteristics, organizational abilities and motivations, and overall environmental factors concerning innovation [55,56]. We have identified four innovation characteristics and four contextual variables (technology competence, company size, competitive demand, and partner readiness) as determinants of post-adoption use, and we postulate that usage serves as an intermediate link to influence firm efficiency. Since variables in the TOE setting can vary across different contexts, additional variables may need to be added for enrichment [57,58].

2.3.2. Technology Context

The technological context sheds light on a technology's endogenous and extrinsic qualities that are essential for its adoption. Complexity is among the elements [59,60]. The organization's propensity to embrace new technology may be strongly impacted by how far it is regarded as improving a certain organizational performance [61]. The extent to which a new idea is thought to be especially hard to understand and put into practice [62,63]. It is appropriate for businesses to examine the benefits of implementing innovations [64], showing how BD uptake is affected by technology characteristics including complexity, compatibility, and opportunism. According to TOE theory, commercial and technical characteristics affect the adoption of technology (BD readiness) [65]. The three qualities of innovation (INN) are complexity (CX), compatibility (CT), and optimism (OP) when the ability of practitioners to perform their tasks is improved by new technology. Therefore, we propose three categories of BD readiness.

The authors of [62] remarked that a new technology or system would probably not catch on if it was deemed to be overly grandiose and difficult to implement. The new technology must be user-friendly to improve the possibility that it will be adopted since it can be difficult, for instance, to change the processes through which they interact [62]. Employees must quickly become knowledgeable about the technology because the adoption process becomes more unpredictable and difficult as technology advances.

According to a study, acceptance of innovation depends significantly on its intricacy [66,67]. Decision-makers are thereby confronted with a conundrum about the acceptance of the technology [68]. Complexity has a weak link with the uptake of new technology when compared to other factors of technological advancement [69,70]. Recent studies on the role of complexity in BD adoption (BDA) have shown that BD complexity negatively impacts adoption [71,72]. Health organizations will be less likely to implement an innovation if they determine that doing so would not require much work. The researchers believe that the following hypothesis is plausible.

Hypothesis 1 (H1). *Complexity has a negative effect on big data readiness in the healthcare sector.*

"Compatibility" refers to the degree to which a new system can be smoothly integrated with the organization's existing system [73]. Adopting technology that is compatible with an organization's culture and business operations is a positive sign [74], revealing that compatibility is a key element influencing the adoption of technology. Ref. [74] revealed that compatibility is a key element influencing the adoption of technology. According to [75], a lack of information on the commercial value that such investments give was mostly to blame for the absence of a connection between BD investment and corporate performance. According to the findings of this study, healthcare organizations are more willing to accept and apply BD in a variety of organizational elements when they understand that BDA adoption readiness is compatible with current organizational procedures and standards. In this work, the following idea is presented.

Hypothesis 2 (H2). *Compatibility has a positive effect on big data readiness in the healthcare sector.*

Relative advantage is "the degree to which an innovation is deemed to be superior to the notion it replaces". The relative advantage encourages the adoption of new technologies. Through trust, it provides the most traceability and provenance of any technology [76]. According to the proposed model, the frequency with which a company uses a cloud computing service is determined by its relative benefit and complexity, as they are the most significant factors. Numerous research studies described the same issue using various terms. For instance, a variety of phrases, including "cloud computing benefit," have been used by academics to characterize the benefits of adopting cloud computing services [77,78]. As a result, considering the nature of cloud computing technology, it is necessary to handle several issues, including complexity, compatibility, and relative benefit. Based on the description above, cloud computing may offer a higher benefit than conventional IT services since it may instantly deliver the necessary computer resources without further investment in computing equipment [79]. Thanks to big data analytics, users inside and outside of an organization can now access integrated data from many sources. In this manner, more components should be included in technological preparedness. It is discovered that relative advantage, compatibility, and simplicity have a beneficial influence on technical preparedness in technology adoption. Big data analytics also includes cutting-edge data management and storage. Data security is thus crucial to big data [80]. As a result, we propose the following.

Hypothesis 3 (H3). *The presence of a relative advantage has a favorable impact on the readiness of the healthcare sector for big data.*

An optimistic perspective of technology may result in a firm belief that it can controllably, adaptably, and efficiently enhance people's everyday life. Most customers who are positive employ developing technologies because they like the excitement of control and the technological experience [81,82]. Prior research has demonstrated that technology readiness (TR) affects an individual's willingness to adopt a technological product or service. Positive factors such as optimism and innovativeness act as drivers to increase motivation to use it, whereas negative factors such as discomfort and insecurity inhibit motivation to use it [83,84].

Those who are less worried about security, on the other hand, believe that technology may be used to protect data. TR has been used a lot and in many different fields, such as self-service technology, construction, wireless technology, internet services, alternative education, and healthcare services. TR contains the traits of optimism, creativity, discomfort, and insecurity. According to Chen [85], after tests and confirmation, added the technology readiness acceptance model (TRAM). The results showed a strong link between TR and behavioral intention in an e-service setting. Other scholars discovered similar results [85–87]. The findings of this study reveal a favorable correlation between technology readiness (TR) and the intention to persistently use personal cloud services. This outcome is in line with earlier research on the adoption of e-service and mobile service technologies.

Hypothesis4 (H4). *The healthcare sector's readiness for big data is positively influenced by optimism.*

Exhibiting the ability "to be a thinking pioneer and an invention pioneer" [88] is how you can tell if someone is creative, and it is assumed that a creative buyer would be willing to take risks when using new ideas. Additionally, since they have an extraordinary level of technical knowledge and a verifiable ardor for spotting innovation, creative buyers are assumed to think that innovation is straightforward [88]. Given that innovative buyers think innovation is intriguing, it stands to reason that innovative buyers would think self-scanners are more important and easier to use than other technologies. Contrary to other TR ideas, it appears that modern BDA researchers have not thoroughly investigated innovativeness.

The TR writing also suggested that for several communicated tests, addressing (i) the unshakeable quality of the measure and (ii) whether the positive outcome had been completed. Experimental research has shown that the innovativeness measure is not viable by any means, primarily because it does not allow for the distinction between general and area-specific innovativeness. Without a doubt, space-specific innovativeness has been advanced as being strongly associated with the selection of innovation, while general innovativeness has been advanced as a flimsy signal of innovation acknowledgment. Recent changes to the innovation preparation record were made in response to this astute issue Ref. [89] revised the measure's assessment. It was discovered during the reevaluation that the measurements' unwavering legitimacy and quality were of great assistance. Thus, the following hypothesis is proposed.

Hypothesis 5 (H5). *Innovativeness has a positive effect on big data readiness in the healthcare sector.*

2.3.3. The Readiness of Healthcare Sectors for Big Data

The expression "technology readiness" pertains to the inclination of customers to use new technologies to achieve their objectives [90]. Another way to think about technological readiness is as an open mindset that welcomes even the most impossible challenges [91]. In other words, a person or organization is more likely to adopt new services and technologies if they are service-ready. Refs. [92,93] advanced an number of presumptions about service readiness and willingness to adopt based on prior research. The technological readiness of a business is influenced by all these elements. Therefore, companies that are more technologically prepared will be better able to use cloud computing technology [79].

Hypothesis 6 (H6). *Big data readiness has a positive effect on the intention to adopt big data in the healthcare sector.*

3. Research Methodology

To confirm the research hypothesis, the testing variables must be computed. The quantitative analysis procedure includes both the design of the survey tool and its evaluation by academic specialists. Quantitative research design determines the theory using statistical analysis. The method was used to gather the data for this investigation, and structural equation modeling employing partial least squares was utilized to analyze the data. Figure 2 depicts a comprehensive diagram of the research design that was implemented.

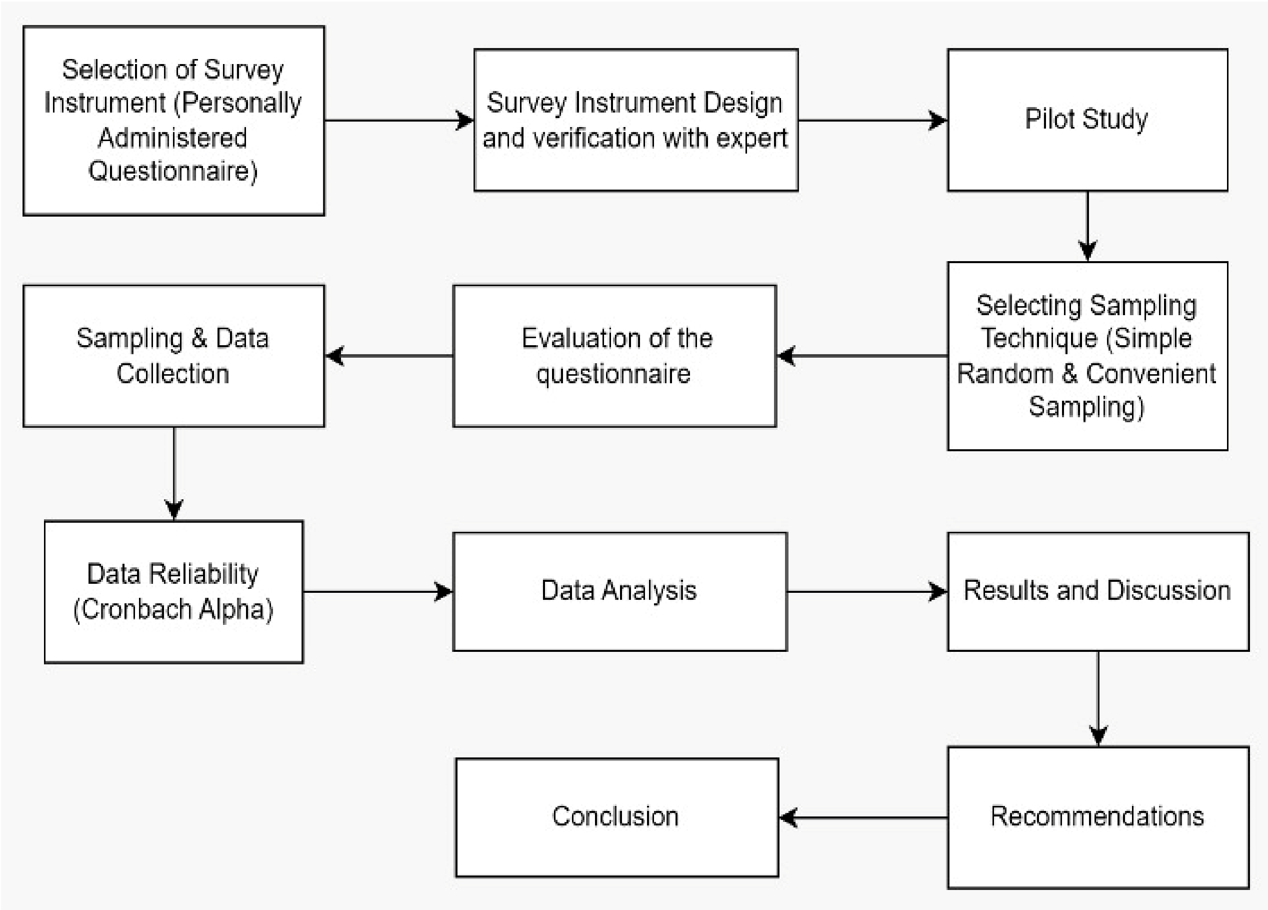

Figure 2. Flowchart of adopted research.

3.1. Pilot Test

The pilot research included 55 doctors, nurses, and other healthcare sector/unit staff who were asked to evaluate the instrument, its general comprehension, and its data-collection effectiveness, in order to ensure that the questionnaire was suitable for use in the healthcare setting and to identify any potential issues or areas for improvement before conducting the formal study. This allowed the researchers to make any necessary modifications and increase the validity and reliability of the questionnaire. After the pilot research, the questionnaire was adjusted and disseminated to Malaysian healthcare consumers as shown in the Table A1. On the other hand, healthcare consumers were selected for the formal study so as to understand their perspective on the use of information technology in healthcare and to evaluate the effectiveness of the proposed intervention from their point of view. As healthcare consumers are the ultimate beneficiaries of healthcare services, their opinions and feedback are essential in improving the quality of healthcare delivery.

The data were gathered using an easy sampling technique. There are two different sampling methods that may be found in the statistics literature: first, probability sampling; second, non-probability sampling. We had a tremendously difficult time using probability sampling to acquire data because of the COVID-19 epidemic. As a result, we chose convenient sampling. Quota sampling and judgment sampling are other divisions of convenient sampling. We need criteria by which to choose the appropriate audience since our research evaluated the considerable data preparedness among health professionals. The judgment sampling process included defining the criteria and gathering the data. The following are the key standards for choosing an audience.

- Health professionals are required to attend;
- A regular user of technology is required for participation;
- Participants must be somewhat familiar with cutting-edge medical technology.

The literature suggests that the G-Power program must be employed to determine the upper limit of the dataset when utilizing non-probability sampling. Accordingly, the researcher conducted a G-Power test to assess the adequacy of the minimal dataset selection. According to [1], the maximum number of arrows pointing to a construct or the research model's independent variables must be taken into account when calculating the minimal limit of sample size. In this research, a construct may have up to eight arrows pointing towards it. The medium impact size, the power of 0.80, and the alpha value of 0.05 ($f^2 = 0.15$) were utilized in the experiment. The majority of social science studies consider 80% to be the minimum acceptable amount to be utilized in the experiment [94,95]. The minimal dataset recommended by G-power should be 102, as in [96]. Since SEM is a method for big datasets, the recommended minimum participant number is over 200. Based on the standards and arguments from the literature, we have chosen the respondents and gathered the information from 50 hospitals in Malaysia. Medical experts were given 550 questionnaires in total. Out of these, 346 individuals responded, and 328 of their total responses were considered useful for the final data analysis.

3.2. Measurement Items

The research on public and private healthcare in Malaysia was undertaken using a simple method called "non-probability sampling". The measurement of the items used a 5-point Likert scale (1 = never, 2 = seldom, 3 = neutral, 4 = often, 5 = always). The objective of this research is to establish a model that will assist businesses in Malaysia, a developing nation, in comprehending the relationships between TOE settings, BD preparedness in healthcare sectors, and a desire to utilize BD in healthcare [97].

4. Data Analysis and Results

The instrument for this research is separated into two sections: (a) demographic characteristics; and (b) components that will be utilized to compute the independent, moderating, and dependent variables. The sections are the result of earlier explorations (Table 1).

Table 1. Descriptive analysis.

Constructs	Mean	Standard Deviation	T-Statistics
Complexity (CX)	4.350	0.035	1.254
Compatibility (CT)	4.371	0.029	4.566
Relative Advantage (RA)	3.783	0.050	2.628
Optimism (OP)	3.663	0.032	2.678
Innovativeness (IV)	3.768	0.052	4.566

4.1. Instrument Design

The information used in this study came from survey tools. We ran a descriptive analysis test first, then a demographic analysis test. Following these, the concept, convergent, and discriminant validity tests were carried out by the researcher [98]. The assertions were rated from "strongly disagree" (1) to "strongly agree" (5) on a Likert scale.

4.1.1. Demographic Data

This research tool is split into two parts: (a) characteristics of the population; and (b) elements that will be used to figure out the independent, influencing, and dependent variables. Previous experiments were used to create the sections [99]. A complete sample of the survey instrument is presented. Demographic details of the respondents are presented in Tables 2–8.

Table 2. Results of the respondents' professional data.

Demographic Variable	Categories	Frequency (n = 328)	Percentage (%)
Gender	Male	208	63.41
	Female	120	36.58

Table 3. Profile of age range.

Demographic Variable	Categories	Frequency (n = 328)	Percentage (%)
Age	21–32	109	33.2
	33–42	75	22.9
	43–52	81	24.7
	53–64	59	18.0
	64 or above	4	1.2

Table 4. Profile of educational level.

Demographic Variable	Categories	Frequency (n = 328)	Percentage (%)
Education	Diploma	38	11.6
	Bachelor	73	22.3
	Master	131	39.9
	Doctorate	86	26.2

Table 5. Profile of position.

Demographic Variable	Categories	Frequency (n = 328)	Percentage (%)
Position	Doctor	65	19.8
	Nurse	118	36.0
	Technician	74	22.6
	IT staff	71	21.6

Table 6. Profile of experience of employees of healthcare.

Demographic Variable	Categories	Frequency (n = 328)	Percentage (%)
Your experience in the current job	1–6 years	117	35.7
	6–16 years	87	26.5
	16–26 years	82	25.0
	26–36 years	42	12.8

Table 7. Profile of information technology competence.

Demographic Variable	Categories	Frequency (n = 328)	Percentage (%)
Information technology competence	Low	87	26.5
	High	241	73.5

Table 8. Profile pf daily usage of computers (hours).

Demographic Variable	Categories	Frequency (n = 328)	Percentage (%)
Daily usage of computers (hours)	4–7 h	146	44.5
	8–11 h	123	37.5
	More than 11 h	59	18.0

This section shows the results of the respondents' geographic, age, job, gender, and level of education information. Furthermore, professional information such as their job title, years of service, computer usage, and experience with information systems is included. These results are discussed in the following subsections.

4.1.2. The Results of Personal Information Collected from Participants

A few of the characteristics that are included in the data include the age, gender, and education level of the people who responded to the survey. As a result, the current study's sample size best covers healthcare, which is the healthcare sector with the highest frequency among Malaysian organizations.

This section provides the background information of the respondents who participated in this survey. Specifically, it gives demographic information on the respondents, including age, gender, educational attainment, employment status, and years of experience. The descriptive analysis used to describe the participants' BD readiness in healthcare consists of four major items as follows. As shown in Table 2, most of the participants (63%) were male teachers, with the remaining 37% being female.

Most respondents, as shown in Table 3, were between the ages of 21 and 32 (33.2%); 22.9% of the population was between the ages of 32 and 42; 24.7% of the population was between the ages of 42 and 52; 18.0% were between 52 and 64 years old; 18.0% were between 52 and 64 years old; and 2.1% were above 64 years old.

Table 4 presents the four different educational periods, and the study revealed that the majority of participants held a master's degree, accounting for 39.9% of the total sample. Meanwhile, the percentage of respondents with a diploma was the lowest among all categories, at 11.6%, while 22.3% held a bachelor's degree and 26.2% held a doctoral degree. The age categories used in the study were based on previous research [100,101]. Additionally, statistics indicate that the proportion of respondents with a diploma is likely to be the smallest compared to other educational levels.

The professional information provided by respondents included their position, experience with computer usage in healthcare, and reasons for not using healthcare. The distribution of the respondents' level of position is shown in Table 5, where doctors (65/328, 19.8%), IT staff (71/328, 21.6%), technicians (74/328, 22.6%), and nurses (118/328, 36.8%) rate it the highest. Nurses were found to be the most frequent respondents in this study and were predominantly female.

Table 6 demonstrates the duration of work experience of healthcare technology employees, indicating that the majority of them (35.7%) had work experience ranging from 1 to 6 years in their current position. Respondents with 6 to 16 years of work experience accounted for 26.5%, while 25.0% of participants had work experience between 16 and 26 years. Only 12.8% of those surveyed had prior work experience of 26 to 36 years.

Table 7 displays the demographic statistics employed in this research, which also revealed that nurses with 1 to 6 years of experience exhibit higher levels of participation compared to other experience categories. Furthermore, they are aware of BD in healthcare at a low rate (26.5) and information technology competence at a high rate (73.5).

Table 8 demonstrates that the response rate for this study is greater between 4 and 7 h, with 146 respondents reporting frequent computer usage in the Malaysian healthcare sector. Moreover, 123 respondents reported daily computer usage (hours) in the same sector, which represents 37.5%. In addition, out of the 59 respondents who reported using computers in healthcare sectors for more than 11 h daily, 18% were included in the aforementioned categories.

4.2. Common Method Bias

The study utilized partial least squares (PLS) analysis via the SmartPLS 3.0 software tool [102]. This approach can be used to analyze the structure and measurement model, and it is preferred because it does not rely on the assumption of normality, which is often not met in survey data [103]. Since the data came from a single source [103,104], researchers looked at the data's whole collinearity to figure out how likely common technique biases were. The complete collinearity test, which asserts that there is no bias from the single-source data collection if the variance inflation factor (VIF) values were less than 3.3, required that all variables be regressed on a common variable. According to the study, all VIF values are below Table 9**.** According to our statistics, a single-source company is thus not a significant issue. The results of the whole collinearity test are shown in Table 9.

Table 9. Full collinearity test results.

CX	CT	IN	OP	RA	BDR
1.041	1.030	1.763	1.028	1.720	1.000

4.3. Measurement Framework

The model was measured using Smart-PLS and the partial least squares (PLS) technique. For the evaluation of measurement models, convergent and discriminant validities were utilized.

Convergent Validity

First, the measurement model's factor loading, construct "reliability, and validity" were assessed. The obtained values for each construct are listed in Table 10. The values of all indicators should be higher than or equal to the corresponding threshold value. Composite reliability (CR), which gauges internal consistency, should be greater than the minimal threshold value of 0.70 [105]. Any concept that has an average variance extracted (AVE) value greater than 0. 5 is considered to be suitable [106]. Utilizing composite reliability, the internal consistency was evaluated. All constructs have reliability coefficients over 0.70, proving their dependability for context-specific measurements. Table 10 further demonstrates that all constructs have AVE values greater than 0.5, which is significant evidence of convergent validity.

Discriminant validity pertains to the statistical and theoretical variations between every pair of constructs [106]. It indicates the degree to which each pair of constructs is distinct from one another in terms of both statistical and theoretical aspects [106]. Heterotrait–Monotrait (HTMT) was used to assess discriminant validity. HTMT is more accurate than the other criteria, as the literature indicated [106]. Table 11 demonstrates that every concept satisfies the requirement for discriminant validity. Ref. [106] demonstrated that the HTMT number should not be higher than 0.85. Additionally, none of the constructions have an HTMT score greater than 0.90, indicating that none of the constructs are discriminately invalid for further investigation. Table 5 displays the HTMT values for each build.

Table 10. Convergent validity.

Constructs	Reliability			
	Cronbach's Alpha	rho_A	CR	AVE
Complexity (CX)	0.805	0.816	0.862	0.614
Compatibility (CT)	0.848	0.981	0.892	0.673
Relative Advantage	0.747	0.748	0.818	0.575
Optimism (OP)	0.796	0.870	0.852	0.539
Innovativeness (IV)	0.834	0.838	0.889	0.668
BD Readiness (BDR) In Healthcare Sector	0.864	0.869	0.902	0.649
Intention To Adopt BD (ITABD)	0.817	0.860	0.877	0.599

Table 11. Discriminant validity (HTMT).

Construct	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Big Data Readiness In Healthcare	0.806						
Compatibility	0.195	0.821					
Complexity	0.141	0.119	0.784				
Innovativeness	0.434	0.026	0.153	0.817			
Intention To Adopt Big Data	0.765	0.111	0.139	0.35	0.774		
Optimism	0.174	0.124	0.043	0.109	0.177	0.734	
Relative Advantage	0.367	−0.018	0.057	0.645	0.364	0.074	0.689

4.4. Structural Model Assessment

Using Smart-PLS, hypotheses are examined in this research study. According to [106], when testing hypotheses, the crucial standards for accepting or rejecting the hypotheses are determined by the path coefficients, confidence intervals, and corresponding t-values, which are computed using a bootstrapping method involving a resampling of 5000 individuals [107]. Furthermore, based on [108], in response to the claim that *p*-values are not a good way to judge the importance of a hypothesis, it was suggested that other measures of statistical significance be used. As in [109], if the *p*-value is between 0.001 and 0.005, the t-value is greater than 1.645, and the confidence interval falls within the same range, then the hypothesis may be accepted. An overview of the criteria we utilized to evaluate the proposed hypotheses is shown in Table 12 and Figure 3.

Table 12. Hypotheses testing results.

Hypothesis	Path	Beta-Value (N = 254)	t-Value Deviation	*p*-Value	f^2	Result
H1	CX -> BDR	0.061	1.332	0.000	0.005	Not Supported
H2	CT -> BDR	0.169	4.456	0.184	0.037	Supported
H3	RA -> BDR	0.162	2.557	0.011	0.020	Supported
H4	OP -> BDR	0.105	2.505	0.013	0.014	Supported
H5	IN -> BDR	0.304	4.395	0.000	0.070	Supported
H6	BDR -> ITABD	0.765	26.716	0.000	1.408	Supported

CX = Complexity; CT = Compatibility; RA = Relative Advantage; OP = Optimism; IN = Innovativeness; ITABD = Intention to adopt big data; and BDR = Big data readiness.

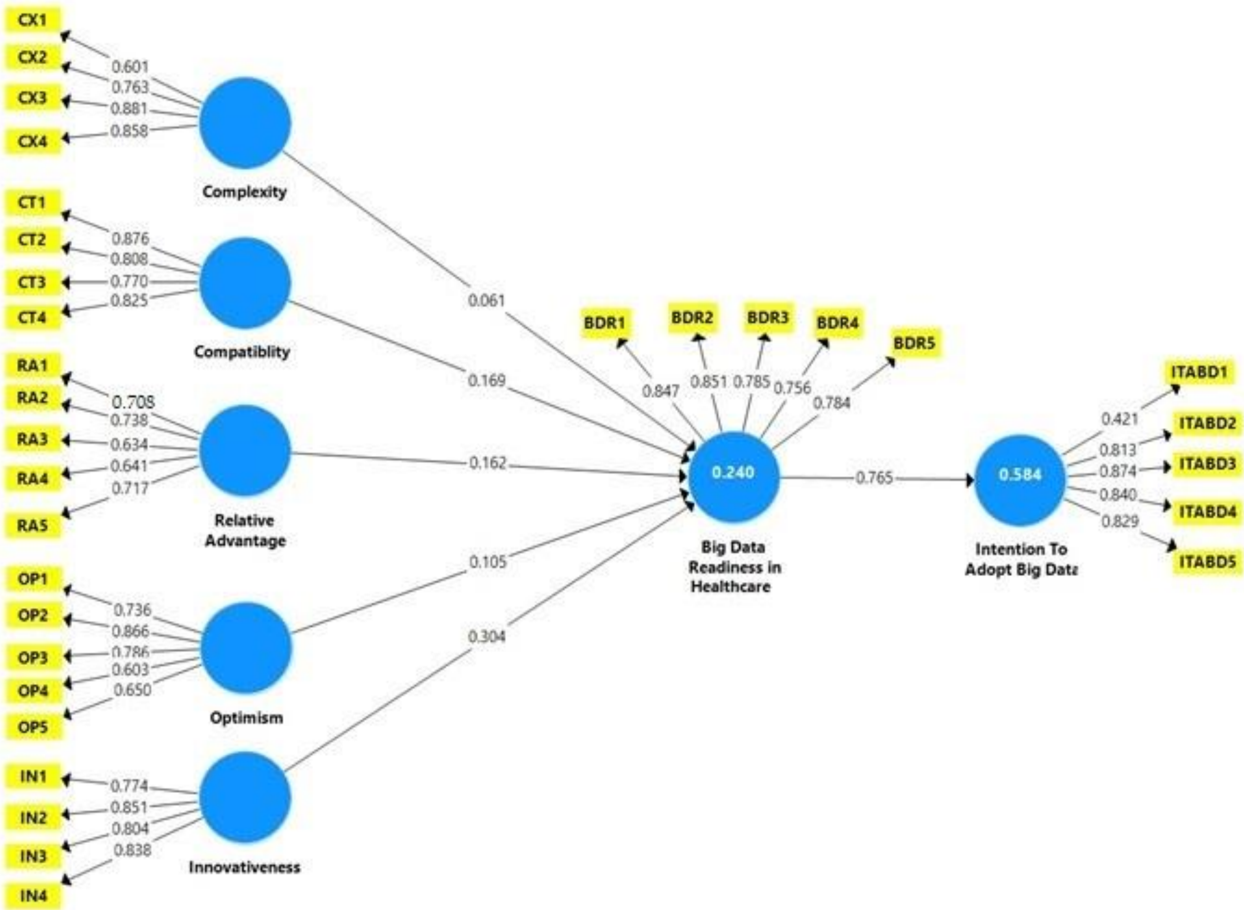

Figure 3. Measurements model.

The results of the data analysis led to the rejection of H1 since the predicted relationship between complexity (CX) and big data readiness (BDR) was not supported by the beta value (0.061), non-significant t values, effect size (f^2), and confidence intervals at the lower and upper bounds. According to [51], the relationship accepts H2 because the beta value of 0.169, the t-value of 4.456, and the f^2 value of 0.037, which indicate a modest impact size, support the link between CT and BDR. With the same range of confidence intervals for the link between RA and BDR's beta coefficient value (0.162), t-value (2.557), and f^2 value (0.020), H3 was accepted.

The hypothesized relationship between OP and BDR suggested a small effect size, which was also found to be significant with a beta value of 0.105, a t-value of 2.505, the same range confidence intervals [0.105–0.50], and an f^2 value of 0.014, so we accepted H4. The significance of the beta value (0.304), t value (4.395), and f^2 value (0.070) further supported H5. For instance, the final relationship's strong t-value (26.716), positive beta coefficient value (0.765), and positive impact size f^2 value (1.408) led to the approval of H6. In our study, all of the barriers that we identified are significant, as demonstrated by their high average ratings. Even the least highly ranked barrier, "Legal and contractual issues," received a moderately average rating. As a result, we believe the level of response we received to be sufficient for this type of research [110,111].

5. Discussion

In this study's empirical literature, an information system was used to talk about BD preparedness in the healthcare field. This research also offered an evaluation of the Malaysian healthcare sector's preparedness for BD. This research provides a thorough framework that expands and contextualizes BD preparedness in healthcare, utilizing technological aspects in healthcare sectors to better understand the models of BD therein.

The comprehensive study's findings will also aid in the development of a framework, tailored to the environment, that can be used to investigate BD persistence in the healthcare industry. The results provide enough proof to back up the claim that apart from complexity, all technological aspects positively affect workers' preparedness for big data technologies.

Technology models have been used to explore how the technological context affects BD readiness, where complexity has a detrimental effect. According to the currently available literature [84,112], complexity difficulties are more significant in developing countries, and virtually all the research reported in the literature has shown their detrimental impact on the readiness of BD technology. Most of the prior research demonstrated that complex challenges are more common in developing nations, and ease of use encourages developing nations to accept new technology and innovation [113]. Therefore, H1 has not been supported since it was out of expectation. In general, complexity can be a significant factor in determining an organization's readiness to effectively manage and leverage big data. The increasing volume, velocity, and variety of data generated in today's digital landscape can make it difficult for organizations to effectively collect, store, process, and analyze these data. This can be particularly challenging for organizations with complex IT systems, legacy technologies, and siloed data management practices. However, the specific impact of complexity on big data readiness may vary depending on several factors, such as the size and scope of the organization, the nature of its IT infrastructure, and the goals and objectives of the big data initiative. In some cases, complexity may be a significant barrier to big data readiness; while in others, it may be less significant or even irrelevant.

As a result, BD technology preparedness in the healthcare industry was greatly impacted by its compatibility with BD's technical qualities [102]; we note the influence of comparative advantage, partibility, complexity, trialability, and observability. In this study, we followed [114]'s recommendations for the three most important factors that have a consistent and meaningful effect on how innovations are used. We investigated the impact of the fit–viability model variables and information on cloud computing adoption in higher education institutions. The relative benefits of e-learning based on cloud computing include vast data storage capacities, access to any application or broadband Internet via any device from any place, and cultural considerations. The following hypotheses will direct our future investigation based on the conceptual framework model we have established and covered previously. Concerning relative advantage, according to [115], an invention's "relative advantage" is "the extent to which the innovation is seen as being superior to the notion it succeeds". Organizations need to understand that embracing innovation can either provide answers to current issues or open new production possibilities such as higher productivity and enhanced operational efficiency.

To make a smart decision about whether to use new technology in a business, you need to think about what benefits it could bring to the business. When a company sees a need for a certain technology, they adopt it because they think it will help them narrow a performance gap or capitalize on a commercial opportunity. Additionally, prior research has shown that relative advantages influence the adoption of technology [116]. Research from the past backs up this conclusion, just like how innovation affects the big data of the participants. These results are explained by the fact that more businesses are turning to big data systems to promote adoption processes by giving individuals access to the majority of the tools and resources they need in order to utilize big data applications [88].

The inducers of technological facilities include optimism, which encourages people to embrace new technology. On the other side, discomfort and insecurity serve as barriers that discourage or delay the adoption of new technology. The inducing and inhibiting aspects of technological facilities function separately, even if they coexist inside of us, and each user may exhibit various combinations of inducing or inhibiting characteristics. To effectively deploy technology inside an enterprise, the manager should understand and enhance the TR of users as public consumers. This result is consistent with the literature on technology adoption that contends that complexity and optimistic characteristics enhance organizational performance in the healthcare sector. The data analysis showed that variables related to the technological setting have a big impact on how healthcare is adopted.

Additionally, they will be crucial in adding actual data to the body of medical literature on BD. The study will establish the groundwork for a comprehensive framework that compares big data readiness with the adoption of other emerging technologies in the healthcare industry and other fields. This research will also aid in the development of a top-notch organization-level framework for healthcare sector settings and related fields. Ultimately, this study is expected to contribute to the advancement of the literature in this domain. Finally, the TOE model was used by the authors in [117] to support their findings that top optimism and simplicity have a favorable impact on acceptance, while complexity has a negative impact.

6. Conclusions

This section includes the authors' concluding comments, the limitations of the study, theoretical contributions, and implications for practice.

6.1. Theoretical Contribution and Implications

The goal of this research was to pinpoint variables that affect how well-liked BD readiness is in developing nations' healthcare systems. By merging technological and business readiness in the healthcare business, a research model was established for this purpose based on the TOE theory used in earlier research. The empirical study provides several significant contributions. First, the results showed that BD readiness was positively impacted by compatibility and technical optimism but not by appropriateness. This suggests that customers may lack confidence in the effectiveness of BD readiness in the healthcare sector; thus, it is important to enhance their perceptions of BD readiness security gradually. Furthermore, the study revealed that complexity, compatibility, and optimism can reduce resistance to the acceptance and readiness of new technologies. It is thus intended to increase trust among healthcare organizations with respect to their embracing of BD, to reduce user difficulties, and to improve use quality in Malaysian healthcare sectors. This is true for both present ICT-related reasons for BD acceptance and BD preparation.

Structural equation modeling was used in this study to analyze the factors that affect BD's readiness to improve the services offered by Malaysia's healthcare sector. The data results show that the healthcare sector's readiness for BD had a significant impact on the healthcare sector in Malaysia. In recent research, the authors demonstrated that readiness for big data adoption has a significant role in BD preparedness. Additionally, research shows that a crucial component of the successful adoption of BD in healthcare systems is the exchange of health information within a vast, interconnected system driven by BD. One must remember that the goal of introducing and employing BD is to enhance the whole patient care experience, not to dominate it. The implementation of BD will result in a considerable decrease in overall IT infrastructure costs, as healthcare providers will not be required to maintain medical information locally; they will just need reliable and constant internet connections—preferably a dedicated leased line for added reliability and validity.

6.2. Practical Implications

The study's conclusions provide important recommendations and considerable ramifications for healthcare practitioners and others who implement BD preparation. The TOE, TRI, BDR, and BD of the healthcare sectors must be connected to these functions for them to be effective. The use of BD in healthcare sectors will be advantageous to practitioners. Second, the results of the research indicate that these distinguishing traits have a significant influence on the healthcare and BD preparation businesses. This research also looks at the impact of ambitions to utilize big data on BD preparation in developing countries' healthcare sectors. This research will provide information to those responsible for implementing BD healthcare sectors in underdeveloped countries, and it will provide suggestions for lowering employee resistance. Finally, this research provides practitioners with a place to start when using BD methodologies to profit from cutting-edge technology in underdeveloped countries such as Malaysia.

It was shown that the relationship between environmental and BD preparation in the healthcare business is significantly influenced by conducive conditions and government IT policy. This illustrates that the government's IT policies are appropriate and help fuel the desire to use big data. Businesses must be proactive in their pursuit of policy for this service and in their suggestions for amendments to pertinent laws and procedures with which to strengthen the government's preparedness to deliver government IT policy. Only government legislation and regulations, however, were shown to have a significant impact on how well-prepared the healthcare sector is for big data. It was proposed that the size of the healthcare organization affected how much of an impact the government's information technology policy had. Therefore, considering that the data were obtained from only one nation (Malaysia), it is crucial, in evaluating this study, to recognize significant cultural variations, particularly those that differentiate between developed and developing nations and influence information system management practices, as well as attitudes towards technology adoption.

The research framework must be enlarged, and samples must be taken from many countries to generalize and revise ideas. Moreover, people's views of certain crucial aspects of adopting new technologies, such as big data, may change depending on their cultural background, and further research into BD might result in more definitive hypothesis testing. While the survey instrument has a sufficient degree of validity and reliability in this area, it does not adequately capture organizational culture and top management support concepts since these are broad variables.

This study shows that economic factors related to the expectation of profitability have a significant impact on the readiness for big data in healthcare sectors, which supports the findings of a previous study [118] Specifically, the study found that the intention to adopt big data increases the expectation of higher profits more than current use of dig data, which affects the readiness for new technologies in healthcare and the intention to use them. However, complexity did not have a significant effect on readiness for big data in healthcare sectors, consistent with the results of a previous study by [26]. The study also suggests that if an organization does not support the goal of embracing dependability through big data, then the expectations for big data readiness preparation would be lower.

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Appendix A

Table A1. Questionnaire items.

Constructs	Items	References
Complexity (CX)		
BD allows me to manage business operations in an efficient way.	CX1	[119–124]
The use of BD is frustrating.	CX2	
The skills needed to improve and use the new technologies are easy for me.	CX3	
The use of BD requires a lot of mental effort.	CX4	
Compatibility (CT)		
The use of BD is compatible with my healthcare corporate culture and value system.	(CT1)	[119,120,122–126]
The use of BD will be compatible with existing hardware and software.	(CT2)	
BD is easy to use and manage.	(CT3)	
BD is compatible with existing emerging technologies.	(CT4)	
Relative Advantage (RA)		
Cloud-based ERP will enhance the efficiency of our company.	(RA1)	[127–129]
Cloud-based ERP will improve the performance of our company.	(RA2)	
Cloud-based ERP will provide timely information for decision making.	(RA3)	
With cloud-based ERP adoption, we expect to see cost savings effect.	(RA4)	
With cloud-based ERP adoption, we will be able to respond quickly and flexibly to our business expansion and pay only for what we use.	(RA5)	
Optimism (OP)		
New technologies contribute to a better quality of life.	(OP1)	[130–134]
Technology gives me more freedom of mobility.	(OP2)	
Technology gives people more control over their daily lives.	(OP3)	
Technology makes me more productive in my personal life.	(OP4)	
Technology makes me more efficient in my occupation.	(OP5)	
Innovativeness		
Innovativeness its big data Opinion leader		[126,135]
Innovativeness tries to use new technology		
Our organization top management actively pursues Innovativeness ideas.		
Our organization gives us a penalty if the proposed idea does not work.		
Our organization accepts Innovativeness well.		
BD Readiness (BDR) in Healthcare Sector		

Table A1. *Cont.*

Constructs	Items	References
The healthcare management understands how they can be used in the healthcare sector.	(BDR1)	[120,126,136–139]
The healthcare IT infrastructure is good (internet service/devices) and can be used for big data.	(BDR2)	
The healthcare management already promoted the usage of the BD to the staff very well.	(BDR3)	
The healthcare staff have the right skills to work with big data.	(BDR4)	
The healthcare IT department and the healthcare management have the right skills to lead the healthcare transformation, and they give very good support to help the staff.	(BDR5)	
Intention to adoption BD (ITABD)		
BD adoption is effective to enhance the behavioral intentions to use the BD analytics system in healthcare.	*(ITABD1)*	[126,136,137,140]
BD technology adoption will increase the performance and effectiveness of healthcare.	*(ITABD2)*	
I would use BD technology adoption to gather health data.	*(ITABD3)*	
I would use the services provided by use BD technology adoption.	*(ITABD4)*	
I would not hesitate to provide information for use BD technology adoption	*(ITABD5)*	

References

1. Ghaleb, E.A.; Dominic, P.; Fati, S.M.; Muneer, A.; Ali, R.F. The assessment of big data adoption readiness with a technology–organization–environment framework: A perspective towards healthcare employees. *Sustainability* **2021**, *13*, 8379. [CrossRef]
2. Bhavnani, S.P.; Parakh, K.; Atreja, A.; Druz, R.; Graham, G.N.; Hayek, S.S.; Krumholz, H.M.; Maddox, T.M.; Majmudar, M.D.; Rumsfeld, J.S.; et al. 2017 Roadmap for Innovation—ACC Health Policy Statement on Healthcare Transformation in the Era of Digital Health, Big Data, and Precision Health: A Report of the American College of Cardiology Task Force on Health Policy Statements and Systems of Care. *J. Am. Coll. Cardiol.* **2017**, *70*, 2696–2718. [CrossRef] [PubMed]
3. Mohamed, A.; Najafabadi, M.K.; Wah, Y.B.; Zaman, E.A.K.; Maskat, R. The state of the art and taxonomy of big data analytics: View from new big data framework. *Artif. Intell. Rev.* **2020**, *53*, 989–1037. [CrossRef]
4. Sun, T.Q.; Medaglia, R. Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. *Gov. Inf. Q.* **2019**, *36*, 368–383. [CrossRef]
5. Vukmirović, A.; Rajnai, Z.; Radojičić, M.; Vukmirović, J.; Milenković, M.J. Infrastructural model for the healthcare system based on emerging technologies. *Acta Polytech. Hung.* **2018**, *15*, 33–48.
6. Wang, Y.; Kung, L.; Byrd, T.A. Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technol. Forecast. Soc. Chang.* **2018**, *126*, 3–13. [CrossRef]
7. Petersen, A.; Tanner, C.; Munsie, M. Citizens' use of digital media to connect with health care: Socio-ethical and regulatory implications. *Health* **2019**, *23*, 367–384. [CrossRef]
8. Merendino, A.; Dibb, S.; Meadows, M.; Quinn, L.; Wilson, D.; Simkin, L.; Canhoto, A. Big data, big decisions: The impact of big data on board level decision-making. *J. Bus. Res.* **2018**, *93*, 67–78. [CrossRef]
9. Quinn, L.; Dibb, S.; Simkin, L.; Canhoto, A.; Analogbei, M. Troubled waters: The transformation of marketing in a digital world. *Eur. J. Mark.* **2016**, *50*, 2103–2133. [CrossRef]
10. Olivo, J.F.L.; Guzmán, J.G.; Colomo-Palacios, R.; Stantchev, V. IT innovation strategy: Managing the implementation communication and its generated knowledge through the use of an ICT tool. *J. Knowl. Manag.* **2016**, *20*, 512–533. [CrossRef]
11. Gantz, J.; Reinsel, D. The digital universe in 2020: Big data, bigger digital shadows, and biggest growth in the far east. *IDC Iview IDC Anal. Future* **2012**, *2007*, 1–16.
12. Chen, M.; Mao, S.; Liu, Y. Big data: A survey. *Mob. Netw. Appl.* **2014**, *19*, 171–209. [CrossRef]
13. Jaseena, K.; David, J.M. Issues, challenges, and solutions: Big data mining. *CS IT-CSCP* **2014**, *4*, 131–140.
14. Gopal, G.; Suter-Crazzolara, C.; Toldo, L.; Eberhardt, W.J.C.C.; Medicine, L. Digital transformation in healthcare–architectures of present and future information technologies. *Clin. Chem. Lab. Med.* **2019**, *57*, 328–335. [CrossRef]

15. Gao, J.; Koronios, A.; Selle, S. Towards a process view on critical success factors in big data analytics projects. In Proceedings of the Twenty-First Americas Conference on Information Systems, Fajardo, Puerto Rico, 13–15 August 2015.
16. Al-Sai, Z.A.; Abdullah, R. Big data impacts and challenges: A review. In Proceedings of the 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT), Amman, Jordan, 9–11 April 2019; IEEE: New York, NY, USA, 2019; pp. 150–155.
17. Alexandru, A.G.; Radu, I.M.; Bizon, M.-L. Big Data in Healthcare-Opportunities and Challenges. *Inform. Econ.* **2018**, *22*, 43–54. [CrossRef]
18. LaValle, S.; Lesser, E.; Shockley, R.; Hopkins, M.S.; Kruschwitz, N. Big data, analytics and the path from insights to value. *MIT Sloan Manag. Rev.* **2011**, *52*, 21–32.
19. Hardin, T.; Kotz, D. Amanuensis: Information provenance for health-data systems. *Inf. Process. Manag.* **2021**, *58*, 102460. [CrossRef]
20. Yang, H.; Guo, X.; Peng, Z.; Lai, K.-H. The antecedents of effective use of hospital information systems in the chinese context: A mixed-method approach. *Inf. Process. Manag.* **2021**, *58*, 102461. [CrossRef]
21. Saleem, M.S.; Isha, A.S.N.; Mohd Yusop, Y.; Awan, M.I.; Naji, G.M.A. Agility and safety performance among nurses: The mediating role of mindful organizing. *Nurs. Rep.* **2021**, *11*, 666–679. [CrossRef]
22. Bai, J. Humanistic Spirit Training of Medical Students Based on Multisource Medical Data Fusion. *Comput. Math. Methods Med.* **2022**, *2022*, 7896367. [CrossRef]
23. Neunaber, T.; Meister, S. Digital Maturity and Its Measurement of General Practitioners: A Scoping Review. *Int. J. Environ. Res. Public Health* **2023**, *20*, 4377. [CrossRef] [PubMed]
24. Amin, I.M.; Hussein, S.S.; Isa, W. Assessing user satisfaction of using hospital information system (HIS) in Malaysia. *People* **2011**, *12*, 13.
25. Salleh, M.I.M.; Abdullah, R.; Zakaria, N. Evaluating the effects of electronic health records system adoption on the performance of Malaysian health care providers. *BMC Med. Inform. Decis. Mak.* **2021**, *21*, 75. [CrossRef] [PubMed]
26. Sarlan, A.; Ahmad, R.; Ahmad, W.F.W.; Dominic, P. Private Healthcare in Malaysia: Investigation on Technology Profiles and Technology Acceptance Factors. *ISICO* **2013**, *2013*, 2013.
27. Zakaria, N.; Yusof, S.A.M. Understanding technology and people issues in hospital information system (HIS) adoption: Case study of a tertiary hospital in Malaysia. *J. Infect. Public Health* **2016**, *9*, 774–780. [CrossRef] [PubMed]
28. Samah, B.A.; Shaffril, H.M.; Hassan, M.A.; D'Silva, J.L. Can technology acceptance model be applied on the rural setting: The case of village development and security committee in Malaysia. *J. Soc. Sci.* **2011**, *7*, 113–119. [CrossRef]
29. Ngai, E.W.; Poon JK, L.; Suk FF, C.; Ng, C.C. Design of an RFID-based healthcare management system using an information system design theory. *Inf. Syst. Front.* **2009**, *11*, 405–417. [CrossRef]
30. Baharuddin, H.E.A.; Othman, A.F.; Adnan, H.; Ismail, N.A.A. Evaluating the Influence of Training on Attitudes to Building Information Modelling (BIM) Adoption in Malaysian Construction Industry by Using Extended Technology Acceptance Model (TAM). In *Collaboration and Integration in Construction, Engineering, Management and Technology*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 577–582.
31. Bakar, N.A.A.; ChePa, N.; Jasin, N.M. Challenges in the implementation of hospital information systems in Malaysian public hospitals. In Proceedings of the 6th International Conference on Computing & Informatics, Akamatsu, Japan, 2–4 August 2017; pp. 636–642.
32. Song, S.; Imai, K.S. Does the hunger safety net programme reduce multidimensional poverty? Evidence from Kenya. *Dev. Stud. Res.* **2019**, *6*, 47–61. [CrossRef]
33. Ho, B.S.; Chui, K.H.; Fong, B.Y.F. Monitoring Elderly Healthcare and Social Services. In *Ageing with Dignity in Hong Kong and Asia: Holistic and Humanistic Care*; Springer Nature: Singapore, 2022; pp. 159–175.
34. Stenberg, K.; Hanssen, O.; Bertram, M.; Brindley, C.; Meshreky, A.; Barkley, S.; Edejer, T.T.-T. Guide posts for investment in primary health care and projected resource needs in 67 low-income and middle-income countries: A modelling study. *Lancet Glob. Health* **2019**, *7*, e1500–e1510. [CrossRef]
35. Cerchione, R.; Centobelli, P.; Riccio, E.; Abbate, S.; Oropallo, E. Blockchain's coming to hospital to digitalize healthcare services: Designing a distributed electronic health record ecosystem. *Technovation* **2023**, *120*, 102480. [CrossRef]
36. Büyüközkan, G.; Göçer, F. Digital supply chain: Literature review and a proposed framework for future research. *Comput. Ind.* **2018**, *97*, 157–177. [CrossRef]
37. Patel, A.B.; Birla, M.; Nair, U. Addressing big data problem using Hadoop and Map Reduce. In Proceedings of the 2012 Nirma University International Conference on Engineering (NUiCONE), Ahmedabad, India, 6–8 December 2012; IEEE: New York, NY, USA, 2012; pp. 1–5.
38. Hilbert, M.; López, P. The world's technological capacity to store, communicate, and compute information. *Science* **2011**, *332*, 60–65. [CrossRef] [PubMed]
39. Rajagopal, S. Data Science: Recent Developments and Future Insights. In *Deep Learning Innovations and Their Convergence with Big Data*; IGI Global: Hershey, PA, USA, 2018; pp. 141–151.
40. Yang, Z.; Sun, J.; Zhang, Y.; Wang, Y. Understanding SaaS adoption from the perspective of organizational users: A tripod readiness model. *Comput. Hum. Behav.* **2015**, *45*, 254–264. [CrossRef]

41. Bag, S.; Wood, L.C.; Xu, L.; Dhamija, P.; Kayikci, Y. Big data analytics as an operational excellence approach to enhance sustainable supply chain performance. *Resour. Conserv. Recycl.* **2020**, *153*, 104559. [CrossRef]
42. Raguseo, E. Big data technologies: An empirical investigation on their adoption, benefits and risks for companies. *Int. J. Inf. Manag.* **2018**, *38*, 187–195. [CrossRef]
43. Troshani, I.; Rampersad, G.; Plewa, C. Adopting innovation management software in university innovation commercialization. *J. Comput. Inf. Syst.* **2011**, *52*, 83–92.
44. Amini, A. A state-of-the-art analysis of innovation models and innovation software tools. In Proceedings of the Conference: 10th European Conference on Innovation and Entrepreneurship, ECIE, Genova, Italy, 17–18 September 2015; pp. 1–9.
45. Saghafian, M.; Laumann, K.; Skogstad, M.R. Stagewise Overview of Issues Influencing Organizational Technology Adoption and Use. *Front. Psychol.* **2021**, *12*, 654. [CrossRef] [PubMed]
46. Luo, X.; Zhang, W.; Li, H.; Bose, R.; Chung, Q.B. Cloud computing capability: Its technological root and business impact. *J. Organ. Comput. Electron. Commer.* **2018**, *28*, 193–213. [CrossRef]
47. Rather, M.-K.; Rather, S.-A. Impact of smartphones on young generation. *Libr. Philos. Pract.* **2019**, *2384*, 1–9.
48. Giotopoulos, I.; Kontolaimou, A.; Korra, E.; Tsakanikas, A. What drives ICT adoption by SMEs? Evidence from a large-scale survey in Greece. *J. Bus. Res.* **2017**, *81*, 60–69. [CrossRef]
49. Subramani Parasuraman, A.T.S.; Yee, S.W.K.; Chuon, B.L.C.; Ren, L.Y. Smartphone usage and increased risk of mobile phone addiction: A concurrent study. *Int. J. Pharm. Investig.* **2017**, *7*, 125. [CrossRef]
50. Baig, M.I.; Shuib, L.; Yadegaridehkordi, E. Big data in education: A state of the art, limitations, and future research directions. *Int. J. Educ. Technol. High. Educ.* **2020**, *17*, 44. [CrossRef]
51. Silow-Carroll, S.; Edwards, J.N.; Rodin, D. Using electronic health records to improve quality and efficiency: The experiences of leading hospitals. *Issue Brief Commonw Fund* **2012**, *17*, 40.
52. Pan, Y.; Froese, F.; Liu, N.; Hu, Y.; Ye, M. The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *Int. J. Hum. Resour. Manag.* **2022**, *33*, 1125–1147. [CrossRef]
53. Wisdom, J.P.; Chor, K.H.B.; Hoagwood, K.E.; Horwitz, S.M. Innovation adoption: A review of theories and constructs. *Adm. Policy Ment. Health Ment. Health Serv. Res.* **2014**, *41*, 480–502. [CrossRef]
54. Tornatzky, L.G.; Fleischer, M.; Chakrabarti, A.K. *Processes of Technological Innovation*; Lexington Books: Lexington, KY, USA, 1990.
55. Naji, G.M.A.; Isha, A.S.N.; Alazzani, A.; Brough, P.; Saleem, M.S.; Mohyaldinn, M.E.; Alzoraiki, M. Do leadership, organizational communication, and work environment impact employees' psychosocial hazards in the oil and gas industry? *Int. J. Environ. Res. Public Health* **2022**, *19*, 4432. [CrossRef]
56. Isha, A.S.N.; Naji, G.M.A.; Saleem, M.S.; Brough, P.; Alazzani, A.; Ghaleb, E.A.; Muneer, A.; Alzoraiki, M. Validation of "Depression, Anxiety, and Stress Scales" and "Changes in Psychological Distress during COVID-19" among University Students in Malaysia. *Sustainability* **2023**, *15*, 4492. [CrossRef]
57. Alzoraiki, M.; Ahmad, A.R.; Ateeq, A.A.; Naji, G.M.A.; Almaamari, Q.; Beshr, B.A.H. Impact of Teachers' Commitment to the Relationship between Transformational Leadership and Sustainable Teaching Performance. *Sustainability* **2023**, *15*, 4620. [CrossRef]
58. Aboelmaged, M.G. Predicting e-readiness at firm-level: An analysis of technological, organizational and environmental (TOE) effects on e-maintenance readiness in manufacturing firms. *Int. J. Inf. Manag.* **2014**, *34*, 639–651. [CrossRef]
59. Kapoor, K.K.; Dwivedi, Y.K.; Williams, M.D. Empirical examination of the role of three sets of innovation attributes for determining adoption of IRCTC mobile ticketing service. *Inf. Syst. Manag.* **2015**, *32*, 153–173. [CrossRef]
60. Baker, J. The technology–organization–environment framework. *Inf. Syst. Theory* **2012**, *1*, 231–245.
61. Gu, V.C.; Cao, Q.; Duan, W. Unified Modeling Language (UML) IT adoption—A holistic model of organizational capabilities perspective. *Decis. Support Syst.* **2012**, *54*, 257–269. [CrossRef]
62. McNaughton, B.L.; O'Keefe, J.; Barnes, C.A. The stereotrode: A new technique for simultaneous isolation of several single units in the central nervous system from multiple unit records. *J. Neurosci. Methods* **1983**, *8*, 391–397. [CrossRef]
63. Bolonne, H.; Wijewardene, P. Critical factors affecting the intention to adopt big data analytics in apparel sector, Sri Lanka. *Int. J. Adv. Comput. Sci. Appl.* **2020**, *11*, 149–162. [CrossRef]
64. Sharma, M.; Gupta, R.; Acharya, P. Analysing the adoption of cloud computing service: A systematic literature review. *Glob. Knowl. Mem. Commun.* **2020**, *70*, 114–153. [CrossRef]
65. Ijab, M.T.; Wahab, S.M.A.; Salleh, M.A.M.; Bakar, A.A. Investigating Big Data Analytics Readiness in Higher Education Using the Technology-Organisation-Environment (TOE) Framework. In Proceedings of the 2019 6th International Conference on Research and Innovation in Information Systems (ICRIIS), Johor Bahru, Malaysia, 2–3 December 2019; IEEE: New York, NY, USA, 2019; pp. 1–7.
66. Harindranath, G.; Dyerson, R.; Barnes, D. ICT in small firms: Factors affecting the adoption and use of ICT in Southeast England SMEs. In Proceedings of the 2008 European Conference on Information Systems, Galway, Ireland, 9–11 June 2008.
67. Kandil, A.M.N.A.; Ragheb, M.A.; Ragab, A.A.; Farouk, M. Examining the effect of TOE model on cloud computing adoption in Egypt. *Bus. Manag. Rev.* **2018**, *9*, 113–123.
68. Asiaei, A.; Rahim, N.Z.A. A multifaceted framework for adoption of cloud computing in Malaysian SMEs. *J. Sci. Technol. Policy Manag.* **2019**, *10*, 708–750. [CrossRef]

69. Alshamaila, Y.; Papagiannidis, S.; Li, F. Cloud computing adoption by SMEs in the north east of England. *J. Enterp. Inf. Manag.* **2013**, *26*, 250–275. [CrossRef]
70. Rowe, F.; Truex, D.; Huynh, M.Q. An empirical study of determinants of e-commerce adoption in SMEs in Vietnam: An economy in transition. *J. Glob. Inf. Manag. JGIM* **2012**, *20*, 23–54.
71. Gangwar, H. Understanding the determinants of Big data adoption in India: An analysis of the manufacturing and services sectors. *Inf. Resour. Manag. J. IRMJ* **2018**, *31*, 1–22. [CrossRef]
72. Lai, Y.; Sun, H.; Ren, J. Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management. *Int. J. Logist. Manag.* **2018**, *29*, 676–703. [CrossRef]
73. Awa, H.O.; Ukoha, O.; Igwe, S.R. Revisiting technology-organization-environment (TOE) theory for enriched applicability. *Bottom Line* **2017**, *30*, 2–22. [CrossRef]
74. Azeem, M.; Ahmed, M.; Haider, S.; Sajjad, M. Expanding competitive advantage through organizational culture, knowledge sharing and organizational innovation. *Technol. Soc.* **2021**, *66*, 101635. [CrossRef]
75. Ren, J.-f.; Fosso Wamba, S.; Akter, S.; Dubey, R.; Childe, S.J. Modelling quality dynamics on business value and firm performance in big data analytics environment. *Int. J. Prod. Res.* **2017**, *55*, 5011–5026.
76. Gangwar, H.; Date, H.; Ramaswamy, R. Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *J. Enterp. Inf. Manag.* **2015**, *28*, 107–130. [CrossRef]
77. Al-Sharafi, M.A.; Arshah, R.A.; Abu-Shanab, E.A. Factors influencing the continuous use of cloud computing services in organization level. In Proceedings of the International Conference on Advances in Image Processing, Bangkok, Thailand, 25–27 August 2017; pp. 189–194.
78. Saleem, M.S.; Isha, A.S.N.; Awan, M.I.; Yusop, Y.B.; Naji, G.M.A. Fostering academic engagement in post-graduate students: Assessing the role of positive emotions, positive psychology, and stress. *Front. Psychol.* **2022**, *13*, 920395. [CrossRef]
79. Ghaleb, E.A.; Dominic, P.D.; Alzoraiki, M.; Mohamed, I.; Naji, G.M.A.; Ammar, A.A. The role of transformational leadership style and intellectual capital in improving the service quality of the public healthcare sector in developing countries–conceptual study. *Int. J. Intellect. Hum. Resour. Manag. (IJIHRM)* **2022**, *3*, 1–7. [CrossRef]
80. Sam, K.M.; Chatwin, C.R. Understanding adoption of Big data analytics in China: From organizational users perspective. In Proceedings of the 2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Bangkok, Thailand, 16–19 December 2018; IEEE: New York, NY, USA, 2018; pp. 507–510.
81. Yoon, J.; Li, S.; Hao, Y. Design-mediated positive emotion regulation: The development of an interactive device that supports daily practice of positive mental time traveling. *Int. J. Hum.–Comput. Interact.* **2022**, *38*, 432–446. [CrossRef]
82. Naji, G.M.A.; Isha, A.S.N.; Alazzani, A.; Saleem, M.S.; Alzoraiki, M. Assessing the mediating role of safety communication between safety culture and employees safety performance. *Front. Public Health* **2022**, *10*, 840281. [CrossRef] [PubMed]
83. Etim, E.; Daramola, O. Investigating the E-Readiness of Informal Sector Operators to Utilize Web Technology Portal. *Sustainability* **2023**, *15*, 3449. [CrossRef]
84. Goutam, D.; Ganguli, S.; Gopalakrishna, B. Technology readiness and e-service quality–impact on purchase intention and loyalty. *Mark. Intell. Plan.* **2022**, *40*, 242–255. [CrossRef]
85. Chen, S.-C.; Li, S.-H.; Liu, S.-C.; Yen, D.C.; Ruangkanjanases, A. Assessing Determinants of Continuance Intention towards Personal Cloud Services: Extending UTAUT2 with Technology Readiness. *Symmetry* **2021**, *13*, 467. [CrossRef]
86. Shim, H.-S.; Han, S.-L.; Ha, J. The Effects of Consumer Readiness on the Adoption of Self-Service Technology: Moderating Effects of Consumer Traits and Situational Factors. *Sustainability* **2021**, *13*, 95. [CrossRef]
87. Adiyarta, K.; Napitupulu, D.; Nurdianto, H.; Rahim, R.; Ahmar, A. User acceptance of E-Government Services Based on TRAM model. In *IOP Conference Series: Materials Science and Engineering, Proceedings of the 7th AIC-ICMR on Sciences and Engineering 2017, Banda Aceh, Indonesia, 18–20 October 2017*; IOP Publishing: Bristol, UK, 2017; p. 012057.
88. Haddad, A.; Ameen, A.; Isaac, O.; Alrajawy, I.; Al-Shbami, A.; Midhun Chakkaravarthy, D. The impact of technology readiness on the big data adoption among UAE organisations. In Proceedings of the Data Management, Analytics and Innovation: Proceedings of ICDMAI 2019, Kuala Lumpur, Malaysia, 18–20 January 2019; Springer: Berlin/Heidelberg, Germany, 2019; Volume 2, pp. 249–264.
89. Ramírez-Correa, P.; Grandón, E.E.; Rondán-Cataluña, F.J. Users segmentation based on the Technological Readiness Adoption Index in emerging countries: The case of Chile. *Technol. Forecast. Soc. Chang.* **2020**, *155*, 120035. [CrossRef]
90. Chong, A.Y.-L.; Chan, F.T. Structural equation modeling for multi-stage analysis on Radio Frequency Identification (RFID) diffusion in the health care industry. *Expert Syst. Appl.* **2012**, *39*, 8645–8654. [CrossRef]
91. Chen, D.Q.; Preston, D.S.; Swink, M. How the use of big data analytics affects value creation in supply chain management. *J. Manag. Inf. Syst.* **2015**, *32*, 4–39. [CrossRef]
92. Marr, B. How big data is changing healthcare. *Forbes*, 21 April 2015.
93. Chong, A.Y.-L.; Liu, M.J.; Luo, J.; Keng-Boon, O. Predicting RFID adoption in healthcare supply chain from the perspectives of users. *Int. J. Prod. Econ.* **2015**, *159*, 66–75. [CrossRef]
94. Gefen, D.; Rigdon, E.E.; Straub, D. Editor's comments: An update and extension to SEM guidelines for administrative and social science research. *Mis Q.* **2011**, *35*, 3–14. [CrossRef]
95. Hair, J.F., Jr.; Hult, G.T.M.; Ringle, C.; Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 2nd ed.; Sage Publications: Thousand Oaks, CA, USA, 2017; Volume 2.

96. Kline, R.B. *Principles and Practice of Structural Equation Modeling*; Guilford Publications: New York, NY, USA, 2015.
97. Dong, K.; Ali, R.F.; Dominic, P.; Ali, S.E.A. The Effect of Organizational Information Security Climate on Information Security Policy Compliance: The Mediating Effect of Social Bonding towards Healthcare Nurses. *Sustainability* **2021**, *13*, 2800. [CrossRef]
98. Premkumar, G.; Ramamurthy, K. The role of interorganizational and organizational factors on the decision mode for adoption of interorganizational systems. *Decis. Sci.* **1995**, *26*, 303–336. [CrossRef]
99. Cabrera-Sánchez, J.-P.; Villarejo-Ramos, A.F. Factors affecting the adoption of big data analytics in companies. *Rev. Adm. Empresas* **2020**, *59*, 415–429. [CrossRef]
100. Gupta, A.C.; Srivastava, A.; Wiita, P.J. Periodic oscillations in the intra-day optical light curves of the blazar S5 0716+ 714. *Astrophys. J.* **2008**, *690*, 216. [CrossRef]
101. Abu-Rub, H.; Holtz, J.; Rodriguez, J.; Baoming, G. Medium-voltage multilevel converters—State of the art, challenges, and requirements in industrial applications. *IEEE Trans. Ind. Electron.* **2010**, *57*, 2581–2596. [CrossRef]
102. Naji, G.M.A.; Isha, A.S.N.; Mohyaldinn, M.E.; Leka, S.; Saleem, M.S.; Rahman, S.M.N.B.S.A.; Alzoraiki, M. Impact of safety culture on safety performance; mediating role of psychosocial hazard: An integrated modelling approach. *Int. J. Environ. Res. Public Health* **2021**, *18*, 8568. [CrossRef]
103. Lin, C.H.; Shih, H.Y.; Sher, P.J. Integrating technology readiness into technology acceptance: The TRAM model. *Psychol. Mark.* **2007**, *24*, 641–657. [CrossRef]
104. Ifinedo, P. An empirical analysis of factors influencing Internet/e-business technologies adoption by SMEs in Canada. *Int. J. Inf. Technol. Decis. Mak.* **2011**, *10*, 731–766. [CrossRef]
105. Hair, J.F.; Sarstedt, M.; Ringle, C.M. Rethinking some of the rethinking of partial least squares. *Eur. J. Mark.* **2019**, *53*, 566–583. [CrossRef]
106. Henseler, J.; Ringle, C.M.; Sarstedt, M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* **2015**, *43*, 115–135. [CrossRef]
107. Ramayah, T.; Cheah, J.; Chuah, F.; Ting, H.; Memon, M. Partial least squares structural equation modeling (PLS-SEM) using smartPLS 3.0. In *An Updated Guide and Practical Guide to Statistical Analysis*; Pearson: London, UK, 2018.
108. Sarstedt, M.; Ringle, C.M.; Hair, J.F. Partial least squares structural equation modeling. *Handb. Mark. Res.* **2017**, *26*, 1–40.
109. Hair, J.F., Jr.; Sarstedt, M.; Hopkins, L.; Kuppelwieser, V.G. Partial least squares structural equation modeling (PLS-SEM). *Eur. Bus. Rev.* **2014**, *26*, 106–121. [CrossRef]
110. Kothari, C.R. *Research Methodology: Methods and Techniques*; New Age International Limited: New York, NY, USA, 2004; p. 401. ISBN 8122415229, 9788122415223.
111. Wahyuni, D. The research design maze: Understanding paradigms, cases, methods and methodologies. *J. Appl. Manag. Account. Res.* **2012**, *10*, 69–80.
112. Hassan, S.T.; Batool, B.; Zhu, B.; Khan, I. Environmental complexity of globalization, education, and income inequalities: New insights of energy poverty. *J. Clean. Prod.* **2022**, *340*, 130735. [CrossRef]
113. Chong, K.W.; Kim, Y.S.; Choi, J. A Study of Factors Affecting Intention to Adopt a Cloud-Based Digital Signature Service. *Information* **2021**, *12*, 60. [CrossRef]
114. Tornatzky, L.G.; Klein, K.J. Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Trans. Eng. Manag.* **1982**, *EM-29*, 28–45. [CrossRef]
115. Mndzebele, N. The effects of relative advantage, compatibility and complexity in the adoption of EC in the hotel industry. *Int. J. Comput. Commun. Eng.* **2013**, *2*, 473. [CrossRef]
116. Mairura, K.O. Relative advantage as a determinant of technology adoption among automobile mechanics in micro and small enterprises in Kenya. *Int. J. Acad. Res. Bus. Soc. Sci.* **2016**, *21*, 86–92.
117. Kock, N. *WarpPLS User Manual: Version 7.0. 141*; ScriptWarp Systems: Laredo, TX, USA, 2020.
118. Kessler, S.R.; Pindek, S.; Kleinman, G.; Andel, S.A.; Spector, P.E. Information security climate and the assessment of information security risk among healthcare employees. *Health Inform. J.* **2020**, *26*, 461–473. [CrossRef]
119. Gutierrez, A.; Boukrami, E.; Lumsden, R. Technological, organisational and environmental factors influencing man-agers' decision to adopt cloud computing in the UK. *J. Enterp. Inf. Manag.* **2015**, *28*, 788–807. [CrossRef]
120. Oliveira, T.; Thomas, M.; Espadanal, M. Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Inf. Manag.* **2014**, *51*, 497–510. [CrossRef]
121. Grönlund, Å.; Islam, Y.M. A mobile e-learning environment for developing countries: The Bangladesh virtual interactive classroom. *Inf. Technol. Dev.* **2010**, *16*, 244–259. [CrossRef]
122. Mansour, R.F.; Escorcia-Gutierrez, J.; Gamarra, M.; Díaz, V.G.; Gupta, D.; Kumar, S. Artificial intelligence with big data analytics-based brain intracranial hemorrhage e-diagnosis using CT images. *Neural Comput. Appl.* **2021**, 1–13. [CrossRef]
123. Maroufkhani, P.; Ismail, W.K.W.; Ghobakhloo, M. Big data analytics adoption model for small and medium enterprises. *J. Sci. Technol. Policy Manag.* **2020**. [CrossRef]
124. Agrawal, K. Investigating the determinants of Big Data Analytics (BDA) adoption in Asian emerging economies. *Acad. Manag. Annu. Meet. Proc.* **2015**, *2015*, 11290.
125. Zhu, K.; Dong, S.; Xu, S.X.; Kraemer, K.L. Innovation diffusion in global contexts: Determinants of post-adoption digital transformation of European companies. *Eur. J. Inf. Syst.* **2006**, *15*, 601–616. [CrossRef]

126. Ho, J.C.; Wu, C.G.; Lee, C.S.; Pham, T.T.T. Factors affecting the behavioral intention to adopt mobile banking: An international comparison. *Technol. Soc.* **2020**, *63*, 101360. [CrossRef]
127. Ashraf, M.; Hoque, R. An illustration of information communication technology (ICT)-mediated innovation–adoption–implementation in rural Bangladesh. *Tékhne* **2016**, *14*, 45–51. [CrossRef]
128. Rogers, E.M. Chapter 1-Elements of diffusion. In *Diffusion of Innovations*; The Free Press: New York, NY, USA, 2003; pp. 1–22.
129. Premkumar, G.; Roberts, M. Adoption of new information technologies in rural small businesses. *Omega* **1999**, *27*, 467–484. [CrossRef]
130. Kim, T.; Chiu, W.; Chow, M.K.F. Sport technology consumers: Segmenting users of sports wearable devices based on technology readiness. *Sport Bus. Manag. Int. J.* **2019**. [CrossRef]
131. Chiu, W.; Cho, H. The role of technology readiness in individuals' intention to use health and fitness applications: A comparison between users and non-users. *Asia Pac. J. Mark. Logist.* **2020**. [CrossRef]
132. Liljander, V.; Gillberg, F.; Gummerus, J.; Van Riel, A. Technology readiness and the evaluation and adoption of self-service technologies. *J. Retail. Consum. Serv.* **2006**, *13*, 177–191. [CrossRef]
133. Parasuraman, A.; Colby, C.L. An updated and streamlined technology readiness index: TRI 2.0. *J. Serv. Res.* **2015**, *18*, 59–74. [CrossRef]
134. Nugroho, M.A.; Fajar, M.A. Effects of Technology Readiness Towards Acceptance of Mandatory Web-Based Attendance System. *Procedia Comput. Sci.* **2017**, *124*, 319–328. [CrossRef]
135. Culliford, A.; Bradbury, J. A cross-sectional survey of the readiness of consumers to adopt an environmentally sustainable diet. *Nutr. J.* **2020**, *19*, 138. [CrossRef]
136. Banerjee, A.; Chakraborty, C.; Kumar, A.; Biswas, D. Emerging trends in IoT and big data analytics for biomedical and health care technologies. In *Handbook of Data Science Approaches for Biomedical Engineering*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 121–152.
137. Caesarius, L.M.; Hohenthal, J. Searching for big data: How incumbents explore a possible adoption of big data technologies. *Scand. J. Manag.* **2018**, *34*, 129–140. [CrossRef]
138. Byrne, B.M. *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming (Multivariate Applications Series)*; Taylor & Francis Group: New York, NY, USA, 2010; Volume 396, p. 7384.
139. Nugroho, M.A. Impact of Government Support and Competitor Pressure on the Readiness of SMEs in Indonesia in Adopting the Information Technology. *Procedia Comput. Sci.* **2015**, *72*, 102–111. [CrossRef]
140. Mukred, M.; Yusof, Z.M.; Alotaibi, F.M.; Asma'Mokhtar, U.; Fauzi, F. The key factors in adopting an electronic records management system (ERMS) in the educational sector: A UTAUT-based framework. *IEEE Access* **2019**, *7*, 35963–35980. [CrossRef]