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The Assessment of Big Data Adoption Readiness with a Technology–Organization–Environment Framework: A Perspective towards Healthcare Employees

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Abstract: Big data is rapidly being seen as a new frontier for improving organizational performance. However, it is still in its early phases of implementation in developing countries' healthcare organizations. As data-driven insights become critical competitive advantages, it is critical to ascertain which elements influence an organization's decision to adopt big data. The aim of this study is to propose and empirically test a theoretical framework based on technology–organization–environment (TOE) factors to identify the level of readiness of big data adoption in developing countries' healthcare organizations. The framework empirically tested 302 Malaysian healthcare employees. The structural equation modeling was used to analyze the collected data. The results of the study demonstrated that technology, organization, and environment factors can significantly contribute towards big data adoption in healthcare organizations. However, the complexity of technology factors has shown less support for the notion. For technology practitioners, this study showed how to enhance big data adoption in healthcare organizations through TOE factors.

Keywords: emerging technologies; big data; technology adoption; healthcare; healthcare transformation; TOE and TRI theories

Citation: Ghaleb, E.A.A.; Dominic, P.D.D.; 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. https://doi.org/10.3390/su13158379

Academic Editors: Osama Sohaib and Muhammad Asif

Received: 24 June 2021
Accepted: 12 July 2021
Published: 27 July 2021

1. Introduction

Healthcare transformation is the result of a unified vision across a diverse group of stakeholders for the future of care delivery and the development of new patient-centered, evidence-based models that prioritize value over volume [1,2]. Newly developed and fast-emerging technology-based innovations play a critical role in this shift [1]. These include digital health with emerging technologies such as cloud computing (CC) and big data analytics (BD), which entail the aggregation of large amounts of structured and unstructured health information and sophisticated analyses using artificial intelligence (AI) [3]; natural language processing techniques [4,5]; and precision-health approaches for identifying individual-level risk and determinants of wellness and pathophysiology [6,7]. BD is the volume of data acquired by health organizations, which is growing exponentially [8].

Furthermore, adopting technologies is necessary for an organization's success and survival [9]. Many firms' IT departments have been focusing on quickly adopting disruptive technology to improve customer experience and efficiency [10,11]. Consequently, many of them struggle to strike a balance between the demand for rapid and agile technology deployment and risk management [12,13]. BD, CC, and the internet of things (IoT) are just a few of the recent technological innovations [14]. A total of 236 emerging technologies were identified by Gartner Inc. over the period 2003 to 2015. Some of these new technologies have the potential to disrupt the competitive landscape and provide firms that adopt with a sustained competitive advantage. In this research, we are focusing on BD adoption in Malaysian healthcare. The rate at which new technologies are adopted has major ramifications for adopting enterprises, technology suppliers, and investors [15].

Many countries use BD to provide services in hospitals, logistics, public works, and manufacturing [16]. BD is used to derive meaningful information from massive volumes of data and forecast shifts based on its intelligence [16]. It is a new industry driver, and technical change digitalization of health services would be analyzed [17,18]. While the importance of BD in improving healthcare is acknowledged and accepted, the literature shows that there is still a lack of agreement on the operational concept of BD in healthcare. As a result, examining meanings from previous experiments allows for the identification of similar components, making the use of BD technologies more complex. According to studies, this is due to a lack of understanding of the suitable algorithm and tool for analysis [19,20]. The large-scale data requirements for teamwork, effective data collection, and the ever-increasing disparate types of user applications complicate data management and pose new problems for resource auto-provisioning, scaling, and scheduling of the computing system underneath it [21,22]. However, the main objective of this study is to provide a framework for predicting the expected duration of competitive advantage due to the adoption of emerging technology and suggest a process for generating technology-specific predictions of the scheduled time. Researchers have shown a growing interest in adopting emerging technologies such as big data technology for organizations like those in the health sector [23,24]. Most of the studies were conducted in developed countries. Only a few of those studies were conducted in the context of developing countries like Malaysia. Motivated by this, we conducted our study based on the Malaysian healthcare context. Additionally, most of the designed frameworks for Malaysian healthcare organizations suffer from a lack of new technology adoption in healthcare sectors [25,26].

Similarly, the authors in [27] indicated that the intention to adopt big data controls in healthcare organizations should be investigated. Similarly, [28] studied the information security (InfoSec) readiness and adoption of new technologies and communications problems in the healthcare sector. They established several frameworks for addressing information security violations in healthcare institutions and demonstrated that non-compliance with emerging technologies is a serious issue. However, because all of the studies were conducted in developed countries, their findings cannot be applied to a developing country like Malaysia. Compared to developed countries, organizations' information security faces a very different climate, including new technologies such as big data belief and control [10]. Authors in [29] have evaluated the Malaysian healthcare sector's security culture and awareness; they concluded that there is an urgent need to investigate the determinants of emerging technologies among Malaysian healthcare organizations [10]. While healthcare organizations are increasing their focus on these technologies to help transform their businesses, many healthcare organizations are still struggling to adopt BD in the Malaysian context [30].

Therefore, the key focus of this study is to investigate and analyze the adoption of BD in the Malaysian healthcare sector. Additionally, it evaluates the Malaysian healthcare sector's contribution to adopt BD based on a survey distributed to several employees in different hospitals in Malaysia.

The remainder of the study is organized as follows: Section 2 is devoted to background information and related work, in which the BD is described. Section 3 highlights the theoretical framework and hypothesis development. Section 4 summarizes the methodology used in the proposed study. Section 5 discusses the results, while Section 6 provides the discussion on the findings. Section 7 provides the conclusions and future work.

2. Background and Related Works

Technology is widely used to provide and distribute healthcare [31]. Emerging technology is often referred to as a complex adaptive system (CAS) and is widely used in the healthcare industry [32]. The rapid growth of new information technology, experimental technologies and approaches, CC, the IoT, and social networks has resulted in massive amounts of produced data in various research fields [33,34]. In public health science, the process for improving medical innovation is still a hot topic [35]. With the influx of BD in recent years, more and more research on the effects of technological change has been conducted, the majority of which is centered on the fields of essential medicine and public health [36,37].

In recent years, developing BD apps has become increasingly relevant. The number of organizations from various industries depends on massive amounts of data [38]. Traditional data methods and platforms, on the other hand, are less effective in the light of BD. The rise of BD provides businesses with unparalleled opportunities to achieve and retain a strategic edge. Many companies have begun to renovate or create new business models to take advantage of the strategic business opportunities embedded in BD, giving birth to the concept of big data business models (BDBMs) [39]. Advanced medical technology, disruptive inventions, and modern communication have increasingly become inseparable from delivering best practice healthcare under the umbrella word "digital health" [40]. Although the cost of treating chronic illnesses is that doctor shortages are looming across the world, the desired change in the system of healthcare and medicine is lagging behind the medical technology industry's rapid advancement. Strict laws, the inability of healthcare stakeholders to adapt, and ignoring the role of societal shifts and the human element in an increasingly technical environment are all slowing down the transformation [41]. With increased access to and use of technology, the possibility of patients relying on an easily available yet uncontrolled technical approach to solve their health challenges is expected to rise. In [42], the authors explore how emerging advances assist and enhance the transformation of the old system of the paternalistic model of medicine into an equitable level relationship between patients and practitioners.

Every hospital saves physical health records on their management system, which are then saved in a local system basis that belongs to a particular healthcare organization. The authors in [43] investigated the use of cloud storage to securely exchange and preserve medical data to solve this challenge. The practitioner will use the stored records to enhance the online patient information system's referral networks. It expands the volume and creates a more transferable medium for sharing medical data. They have outlined several challenges in terms of creating a medical record, storing medical data, and exchanging medical data through cloud services. Furthermore, the issues around cloud-based medical image sharing, as well as existing implementations, their limitations, and future directions, are discussed [44]. The findings revealed that exchanging medical data on a cloud substructure is possible, cost-effective, and more versatile in application. However, the paper makes no mention of the topic of BD in CC. Additionally, the journal collection process is unclear; only a few papers are checked, open topics are not addressed, no comparisons between publications are made, and newly published articles do not discuss [9].

Consequently, apart from clinical data, a vast number and diversity of health-related data are now available in digital form, including omics data, socio-demographic data, and insurance claims data [45]. As businesses are forced to change their management structures and skills continuously, Digital Business Transformation (DBT) is a tactic that is gaining traction. DBT encourages innovative ways of thinking and client experiences, resulting in the emergence of new business models [46]. While this high-quality healthcare data could improve service delivery, it is now perceived as a by-product of healthcare delivery rather than a key asset base for strategic advantages [47]. There is a need to turn raw data into usable and actionable information because electronic health data are largely underutilized and therefore discarded [48]. For non-expert audiences, the current report offers a broad description of BD and the effectiveness of healthcare BD. Then, to preserve patient privacy, this article constructs a distributed architecture of structured healthcare model [49].

To be effective, healthcare transformation impacts advancing the organization's goals like HIS and creating new objectives for others who have yet to be created—enabling the effective and exclusive use of computers in healthcare [50,51]. Digital workflows and databases are considered one of the foundations of public healthcare since everything in the healthcare field relies on records [52]. To date, there is not enough research on health in developed and developing countries from these results; it follows that disruptions and concerns about consistency are prevalent during the rapid transition. The introduction of new operating systems and the company's adaptation to this revolution decide the outcome. It was therefore confirmed that the data and death records remained as reported previously. Moreover, our thinking electronic management record system (EMRs) currently has an over 50% failure rate, mostly due to inadequate comprehension and use [53]. The time has arrived to focus on developing healthcare programs that promote public health change is revealed in this issue [54]. Efficiency and organization considerations can also be accounted for when investigating healthcare transition factors [50,55]. This is essential to new technologies. It is incumbent upon the hospitals to regularly reassess their testing procedures to detect healthcare infrastructure vulnerabilities and strengthen [56].

The speed at which large data can be mined and analyzed is a critical factor [29]. High-speed computing is available via CC, distributed computing, and supercomputers. [57,58] are two well-known cloud systems for parallel processing and data analysis. The models have been introduced various data-mining algorithms based on the map-reduce programming paradigm have been proposed [59]. Apache Spark is a high-performance cloud platform for data mining and deep learning. Data is cached in memory in spark, and iterations for the same data are performed directly from memory [60] and demonstrated how to use spark to act fast and immersive analytics on Hadoop information. In the following sections, the challenges in the adoption of BD in healthcare organization will be discussed:

2.1. Healthcare, Big Data, and Challenges

BD presents several technical problems. BD in healthcare is essential because it can be used to forecast illness outcomes, avoid co-morbidities and death, and reduce medical treatment costs. BD has become a valuable database in many countries, where knowledge produced can be used for disease prevention and management. The emphasis on BD in Malaysia has begun, with some programs to exchange patient medical records and expertise between public and private hospitals and clinics. Nonetheless, there are numerous obstacles to integrating BD in healthcare, including privacy, protection, norms, governance, data aggregation, data accommodation, data classification, and technological integration. Before BD can be efficiently applied in healthcare, these issues must be addressed [61]. In health informatics, BD can be used to forecast the results of illnesses and epidemics, boost care and quality of life, and reduce disease progression and premature deaths [62]. BD also provides insights into illnesses and warning signals that can be used to guide care [62]. Not only can this continue to prevent co-morbidities and death, but it will also help the government to save the money on medical care [61]. It is beneficial in clinical medicine for diagnosis and identification and epidemiological science because BD can provide a large volume of data. The government will use the data, non-governmental organizations, and pharmaceutical firms to implement programs, plans, interventions, or medical treatments such as drug production. Patients, clinicians, analysts, and health experts are all affected by BD in healthcare [63].

According to the 2015 Malaysia National Health and Morbidity Survey, the number of obese Malaysians has increased to 17.7% from 4.4 percent in 1996, and 17.5 percent of those aged 18 and up have diabetes, up from 11.6 percent in 2006. This raw data information must be captured and analyzed to provide greater healthcare, accessibility, availability, and continuity of care from diagnosis to treatment and follow-up [61]. The Malaysian Health Data Warehouse (MyHDW) was introduced in 2017 by the Ministry of Health Malaysia (MoH) to exchange patient medical records and expertise between public and private hospitals and clinics. MyHDW seeks to synchronize medical data from public hospitals (including university hospitals and armed forces hospitals), private hospitals and clinics, and the National Registration Department (NRD), the National Department of Statistics, and other health-related departments so that healthcare providers can make informed treatment decisions. The majority of the time, patient evidence is gathered in silos in their respective healthcare centers and is governed and regulated by the administrative divisions of hospitals or clinics. If BD is successfully applied in Malaysia, inefficient overheads will be reduced, and efficient management will be achieved. Most of the time, patient evidence is gathered in silos in their respective healthcare centers and is governed and regulated by the administrative divisions of hospitals or clinics. If BD is introduced successfully in Malaysia, it can reduce unnecessary overheads and improve management effectiveness [64].

Most innovative and cutting-edge innovations are often referred to as "dual-use technologies" as their use/application can be helpful as well as sinister [65]. According to Boyd and Crawford, technology is neither positive nor evil, nor is it neutral; instead, it is the relationship between technology and culture that can have detrimental environmental, social, and human implications. The application of research and technology to healthcare presents significant obstacles, and the legal landscape is becoming more dynamic [66]. It has been suggested that inventions should be classified based on their effect on people and culture [67]. BD affects three classes of people: those who (i) make, (ii) compile, and (iii) analyze data [68]. Another group that can benefit from BD processing can also be identified. Individuals are classified as consumers, citizens/patients, or researchers in the case of healthcare. Users may be employees of medical healthcare institutions who oversee generating or maintaining these results, while researchers are the ones who analyze them. The word "class" refers to the general population that may be affected by healthcare data in any way. We suggest and use a three-dimensional model (Figure 1) in this paper to describe the connections between the use of BD in healthcare, legal problems and concerns, and the individuals who could be impacted; [31,66] used a related model to investigate the emergence of bio-objects' because of advances.

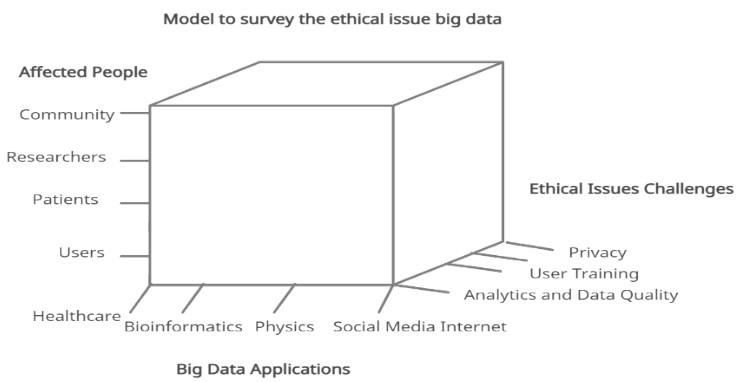

Figure 1. The base concept of legal questions and BD. It shows the many factors that bear on the situation. They are interdependent.

2.2. Theoretical Background

This study is based on two theories, which are technology–organization–environment (TOE) and the Technology Readiness Index (TRI). The TOE framework is a conceptual framework that enables an understanding of how technology and information systems are adopted in an organizational context rather than individually [62]. Furthermore, the TOE model combines innovation theory to help explain how organizations absorb technology and information systems [69–71].

2.2.1. Technology–Organization–Environment (TOE)

TOE framework is able to provide a different perspective on IT adoption by taking into account the technological, organizational, and environmental contexts [72]. The analysis of contingency variables influencing firm decisions is one of the most comprehensive approaches to studying creativity [73]. Such considerations can be grouped into infrastructure, TOE, and organizational effects to justify the results in organizations [74]. The TOE system can be used for the systematic study of innovation effect within an organization. According to [75], TOE aids in the differentiation of inherent creativity characteristics, organizational capacities and motives, and general environmental aspects concerning innovation. As determinants of post-adoption use, we identify four innovation characteristics and four contextual variables (technology competence, company size, competitive demand, and partner readiness) and postulate usage as an intermediate link to influence firm efficiency. Since the variables in the TOE setting can vary from one context to the next, certain additional variables must be added for enrichment.

2.2.2. Technology Readiness Index

The TRI dimension was created by Parasuraman to assess a company's preparedness to adopt new technology. A positive sense of confidence and optimism is the optimism factor, the belief in the use of technology to make one's job easier. Users will be more likely to feel the cloud if they have an optimistic perspective. Computing is both simple and useful. It will then direct users to the next step to improve the performance and quality of work [76]. Parasuraman presented technology preparedness (2000) as "customers' eagerness to adopt new technologies for enhancing their efficiency in life and work" [77]. The first is a promising hypothesis that may be utilized by all parties to understand how people embrace new technologies [77,78].

Academically, readiness has been described as the worker's technical preparedness for technological acceptance, and relevant research has been undertaken [79]. Technology readiness is defined as a person's proclivity to acquire new skills to accomplish their personal and professional goals [79]. Recently, however, research on preparedness has been applied to the service sector in ways beyond technology. The study's findings indicated that preparation had a beneficial influence on perceptions of new services' usefulness, ease, and pleasure [71]. As a result, these two factors contribute to an enterprise's technical preparedness. As a result, increased technological preparedness can quickly and simply embrace cloud computing services [80]. Optimism and creative qualities are identified as factors that aid in TR technology adoption readiness, whereas discomfort and insecurity hold back TR implementation readiness.

Table 1 demonstrates how scientific authors have approached this issue from a variety of angles and sought to represent the services provided by emerging technologies. Despite this data, gaps/lack in research at the organizational level remain evident [81,82]. Although Table 1 summarizes the prior research on the adoption of emerging technologies, this study is founded on organizational-level ideas, which aligns with the research's aims.

2.2.3. Organizational Factors in Big Data Readiness

The characteristics of an organization are signified by the organizational context, such as the organization size, degree of complexity of management or organization structure, and human resources. Lastly, industrial structure, competitors, and government policies are part of the environmental context. The TOE framework is the only framework used to investigate the adoption from technological, organizational, and environmental perspectives [83]. Additionally, there is substantial empirical support in the literature for examining the adoption of new technologies using the TOE framework. We included two constructs under "technological factors": cost and security concerns [84]. We emphasize in this research that cloud technology can result in cost savings through economic utilization. Similarly, security concerns may limit the use of cloud technology. As a result, we are including these two factors as technological variables in this study. These factors will determine whether cloud-based services are cost effective and address any security concerns. Under the heading "organizational context" our model incorporates three constructs that are believed to have an effect on the adoption process: top management support, organization size, and employee knowledge. Support from top management is critical for cloud adoption because it directs the allocation of enterprise resources and the integration of organization services. Similarly, the organization's size is another organizational factor.

Large organizations have an advantage over smaller organizations because they have more resources and are willing to take on additional risks associated with innovation adoption. The employees' knowledge is the third organizational factor.

2.2.4. Environment Factors in Big Data Readiness

The environmental factors (TOE) framework in HIT/eHealth adoption readiness in public healthcare organizations in Ghana. The technology–organization–environment (TOE) framework assumes a broad group of factors to envisage the prospect of IT adoption [85]. The theory posits that adoption is influenced by technological development, organizational conditions, business and organizational reconfiguration, and the industry environment [85]. The perspective of TOE has been successfully used to comprehend important appropriate factors that decide IT innovation at the organizational level, and HISs is no exception [86,87]. Technology adoption refers to an individual's or organization's voluntary decision to adopt and use a technology to solve daily problems [88]. In the context of technology, it has been used to evaluate the IT readiness, technological integration, and security application of websites [89–91]. Technologically, the theory states that technology acceptance is contingent upon the collection of technologies both internal and external to the firm, as well as the perceived relative advantage, compatibility, complexity, trialability, and observability of the application [74,92]. These factors are identified based on the DOI theory [93]. Perceived relative advantage refers to "the degree to which an innovation is perceived as being better than either the status quo or its precursor" [93]. For the adoption of the innovation to be effective, key stakeholders in the organization must recognize the relative advantage in using the innovation [93,94]. Compatibility refers to "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential units of adoption" [93]. Contrary to "ease of use" in the IT adoption literature [95], complexity refers to "the degree to which an innovation is perceived as relatively difficult to understand and use" [93]. The technological characteristics have been used for understanding technology adoption [96]. The context of technology in this model includes the internal and external technologies relevant to the implementation of eHealth/HIT in hospitals [86]. Hospitals implementing eHealth should ensure that relevant internal ICT infrastructure–current (legacy) systems such as HAMS, as well as market-available software and hardware are available and compatible with both incremental and synthetic innovations, given that the deployment of new technologies may alter working or clinical procedures.

For the "environmental context", two constructs were adopted: government regulation and information intensity. Government regulations have the potential to either encourage or dissuade companies from adopting cloud technology. For instance, legislators in the United States and European Union member states have specific responsibilities for the protection of regulatory data. When the government requires enterprises to adhere to cloud-related criteria and protocols, enterprises will be more willing to adopt cloud-based services. The other environmental factor that may influence cloud technology adoption is information intensity. Organizations in more information intensive environments are more likely to adopt new technologies than those in less information-intensive environments. Therefore, the intensity of information from products or services in an organization's environment may have an impact on the cloud adoption [97]. Table 1 shows the summary of existing works for the adoption of Emerging technologies.

Table 1. The adoption of emerging technologies a summary of existing research.

Study	Title	Theory	Method	Findings	Limitations
[71]	A Study of Factors Affecting Intention to Adopt a Cloud-Based Digital Signature Service	TOE	Survey	Management collaboration and support influence suitability. The invention has no evident influence on service readiness or appropriateness. This confirms Parasuraman's results.	Study was conducted in a developed country.
[10]	The Effect of Organizational Information Security Climate on Information Security Policy Compliance: The Mediating Effect of Social Bonding towards Healthcare Employees	TPB and others	survey	The top management increases social IS activities that help staff attitudes towards ISPC.	Data obtained solely from public hospitals, 30 out of 120 institutions.
[98]	Continuance Use of Cloud Computing in Higher Education Institutions: A Conceptual Model	TOE, DOI, IS UTAT, TAM, and others	survey	The current study investigated the most important reasons why HEIs employ CC services.	Study was done in a developed country.
[99]	Investigating the adoption of big data analytics in healthcare: the moderating role of resistance to change	TTF and TAM	Survey/quantitative	It is revealed that technological and organizational factors are the most significant predictors of BDA adoption in the context of SMEs.	A small number of variables were investigated.
[100]	Big data analytics adoption model for small and medium enterprises	TOE	Survey	The data indicate that TOE circumstances have a considerable impact. BDA adoption has a beneficial influence on its adoption, and BDA adoption increases the performance of SMEs.	The study was conducted in a developed country.
[101]	Factors Affecting the Adoption of Big Data Analytics in Companies	UTAUT	survey	Behavioral intent to use BDA in companies.	This research did not include organizational culture, factors that may affect the amount of adoption of this method.
[102]	Determinants Factors of Intention to Adopt Big Data Analytics in Malaysian Public Agencies		Survey	To identify the critical model, which public agencies would find beneficial in funding decisions and when creating outreach initiatives.	Small dataset for analysis
[103]	Adoption of BD analytics in construction: development of a conceptual mode	TOE	Survey	Will allow managers (e.g., IT/IS managers, and business and senior management) to understand the driving forces behind construction BD adoption and plan their own BD adoption.	Only three adoption criteria and creates a new conceptual model to study developing technology acceptability.
[80]	A multifaceted framework for adoption of cloud computing in Malaysian SMEs	TOE, DOI, and TAM	survey	Intentions to use cloud computing can operate as a mediator between TOE variables and cloud computing adoption.	This study included a single informant for each enterprise. The subsequent research may examine the micro-foundations of routines.
[104]	Revisiting technology–organization–environment (TOE) theory for enriched applicability	TOE	survey	Indicate that elements in the technical, organizational, and environmental contexts all have a direct statistically significant link to adoption; hence, adoption is more influenced by T–O–E variables than by individual characteristics.	Extended data are needed to apply the findings to different sectors, industries, and nations and to include the implementation and post-adoption stages and business-to-business (B2B) adoption to construct a more holistic framework.
[105]	Monitoring information security risks within the health care	NA	survey	Inadequate procedures of healthcare employees cause most security breaches.	A study was done in a developed nation and mostly tech issues and solutions.

3. Theoretical Framework and Hypothesis Development

The literature was evaluated in this study to highlight significant findings from prior studies and to serve as a foundation for developing the research framework. Many pertinent papers were reviewed during the literature review phase, and it was discovered that the spread and acceptance of information technology innovation have been extensively investigated and are one of the most developed sectors within the information technology sector [106,107]. The major studies on IT innovation examine the contextual factors that influence the readiness to accept BD [108,109]. According to [109], due to the complexity and context-sensitivity of adoption technology, several technological, organizational, and environmental aspects may vary amongst innovations [110].

Additionally, adopters' cultural and social backgrounds should be considered during the innovation adoption process since they might affect the technology's eventual success or failure [111]. Between industrialized and developing countries, the economic and sociocultural structures of cloud computing adoption vary significantly. Earlier research has demonstrated the critical role of sociocultural components and values in adopting technology across many social systems [112].

Today, developing countries benefit from increased access to new technology because of the increasing usage of mobile phones and smartphones, which positively affects their social growth [113]. Additionally, recent research has demonstrated a beneficial correlation between smartphone use and economic development [114]. In this regard, previous research has shown that simply expanding smartphone usage will not suffice to close the existing technological divide in underdeveloped nations [115]. The delivery models and virtualized nature of emerging technology make it significantly different from other technologies. BD cannot be assessed based on a human interaction viewpoint, while through the use of other technologies such as computers and mobile phones, this evaluation can be performed. Today, studies in BD place a strong emphasis on healthcare [116]. BD services, primarily electronic health records, are among the most acceptable ways for healthcare to capitalize on emerging technology's promise without incurring the quality and management costs associated with on-premises systems and capital expenditure [117].

Figure 2 shows a research model that looks at the relationships between technology, organization, environmental conditions, and the utility of new technologies, and the impact of healthcare preparation on these factors. The technical background variables of compatibility, knowledge quality, and device quality are hypothesized to have major effects on the dependent variable, BD acceptance, and support from upper management. The operational background variables of financial assistance and training are thought to affect the technology preparation independent variable substantially. Compatibility and Complexity Government IT policies, government regulations, and legislation that reflect the environmental background and were hypothesized to significantly impact BD adoption were hypothesized to affect BD adoption substantially. The effect of these variables on BD adoption. The analysis model yielded the following series of hypotheses.

A priori assumptions in the form of hypotheses were generated based on a positivist, deterministic philosophical framework to aid model validation through subsequent statistical analysis. The propositions focus on the relationship between independent variable 1, which includes the technological model, and dependent variables 2 and 3, which intend to adopt BD.

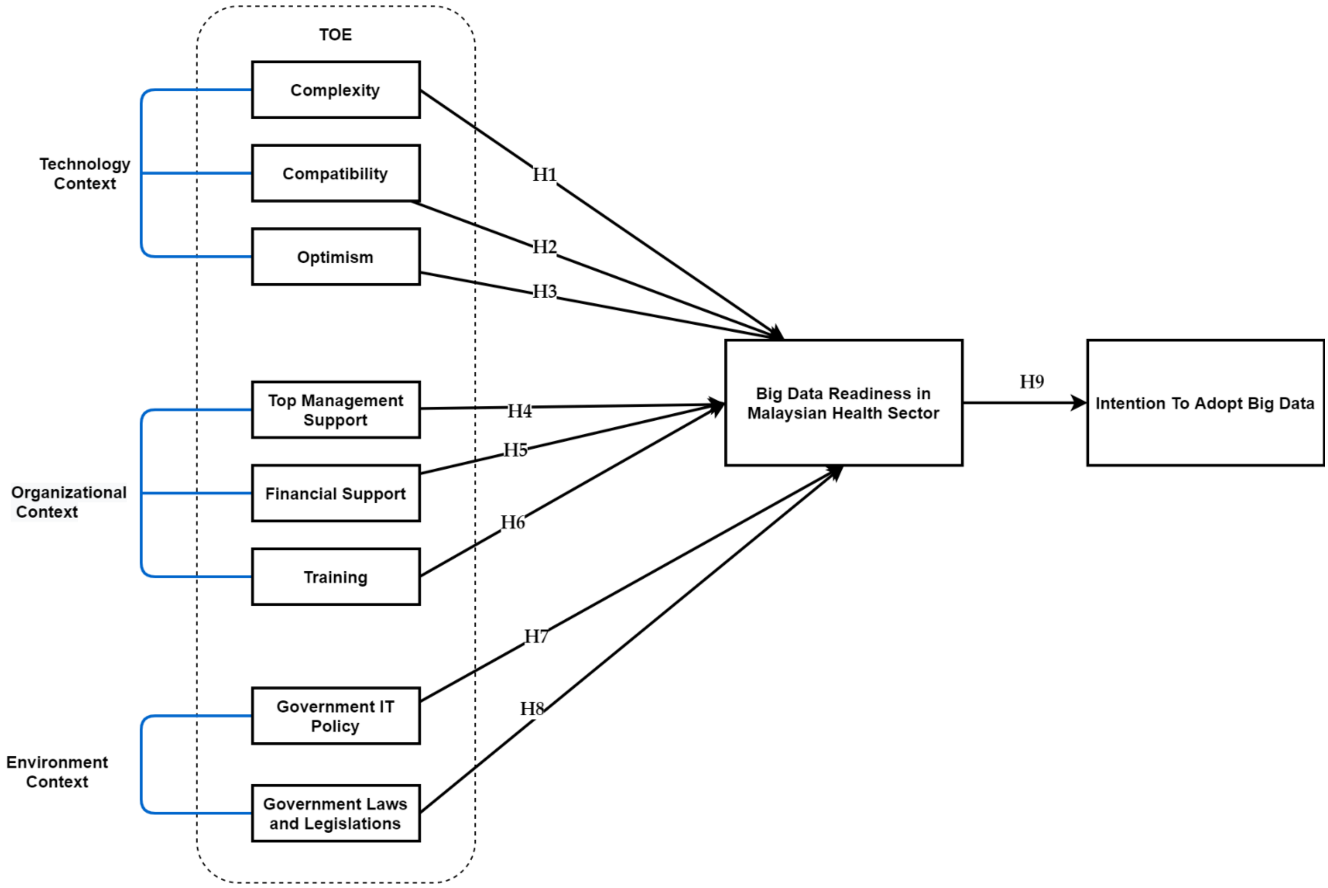

Figure 2. The proposed research framework. For big data adoption in healthcare.

3.1. Technology Context

The technical context illuminates the endogenous and external characteristics of a technology that are necessary for its adoption. Complexity is one of the components [118,119]. The perceived benefit of the new technology to the particular organizational performance may significantly impact the organization's inclination to adopt [120]. Complexity is defined by Rogers (1983) as "the extent to which an invention is seen as being particularly difficult to comprehend and implement" [121,122]. It is reasonable that firms take into consideration the advantages that stem from adopting innovations. In [123], it is shown that technological features such as complexity, compatibility, and opportunism all influence the adoption of BD [71,100,124]. According to TOE theory, technical and commercial features influence the adoption of technological BD readiness [82]. When practitioners' capacity to conduct their jobs is enhanced by new technology., complexity (CX), compatibility (CT), and optimism (OP) are the three characteristics of innovation. As a result, we suggest three hypotheses for BD readiness.

Authors in [121] stated that if a new technology or system is thought to be excessively grandiose and challenging to deploy, it will likely fail to gain traction. There are difficulties, for example, in altering the procedures through which they interact, and hence the new technology must be simple to use to increase the likelihood of adoption [121]. Employees must rapidly gain expertise about a new technology, since the more advanced the technology, the greater the unpredictability and complexity of the adoption process.

As research has revealed, complexity is a significant element in accepting an invention [125,126]. As a result, decision-makers are faced with a dilemma about the adoption of the invention [80]. Compared to other aspects of technological innovation, complexity does not have a significant correlation with the adoption of new technology [127,128]. Recent research on the function of complexity in BD adoption (BDA) has discovered that the complexity of BD has a detrimental effect on its adoption [129,130]. If health organizations believe that adopting an innovation would not involve significant effort, they will be less inclined to do so. According to the researchers, the following theory is possible.

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

Compatibility assesses the degree to which a new system is compatible with the company's existing system [104]. The compatibility of technology adoption indicates its congruence with an organization's culture and business processes; [124,131] found compatibility to be a crucial factor in driving technology adoption. According to [132], the absence of a link between BD investment and company success was mostly owing to a lack of relevant data on the business value provided by such investments [132,133]. This study reveals that healthcare organizations are more receptive to accepting and implementing BD in various aspects of their organization if they realize that the BDA adoption readiness is consistent with existing organizational processes and standards. The following notion is advanced in this study.

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

A favorable attitude toward technology may result in a solid view that technology may improve people's daily lives in terms of control, flexibility, and efficiency [71,134–136]. By and large, optimistic consumers embrace emerging technologies because they value the experience of technology and the thrill of control. Prior research has demonstrated that TR influences one's willingness to use a technology product or service, with drivers (i.e., optimism and innovativeness) favorably influencing the desire to use and inhibitors (i.e., discomfort and insecurity) influencing adversely [136–138]. However, those who are less concerned about security feel that technology may be utilized to safeguard data. TR encompasses the characteristics of optimism, inventiveness, discomfort, and insecurity, and it has been widely implemented in fields such as self-service technologies, the building sector, wireless technology, internet services, educational options, and healthcare services. Lin et al. [136] combined the technology readiness acceptance model (TRAM) and discovered a substantial association between TR and behavioral intention in an e-service environment after testing and verification. Other academics found comparable findings [77,136,139,140]. According to the relevant e-service and mobile service adoption studies discussed before, this study posits a positive relationship between TR and the desire to continue using personal cloud services and hypothesizes:

Hypothesis 3 (H3). *Optimism has a positive effect on big data readiness in the healthcare sector.*

3.2. Organizational Context

In this study, management support and organizational preparedness were regarded as factors affecting healthcare organizations' BDA adoption. The term "top management support" refers to the extent to which managers grasp and embrace a new technology system's technological potential [141,142]. In structural equation models (SEMs), decision-makers are extremely likely to be members of the senior management team, and their backing is important for an innovation's acceptance. Indeed, they constitute the primary link between individual and organizational technology adoption since adoption tends to correlate with the amount of innovativeness of top managers or leaders. Previous research has established top management support [143]. In the setting of small and medium-sized businesses, senior management was less willing to deploy new systems [80,100,122]. Thus, the following hypothesis is suggested, considering the previous reasoning.

Hypothesis 4 (H4). *Top management support has a positive effect on big data readiness in the healthcare sector.*

Four critical aspects in the ability dimension are financial support, data skills, data resources, and technical capacity. The findings indicated that all facets of capability are critical for BD adoption. To capitalize on BD, businesses must execute a set of procedures, including data collecting, storage, transfer, and analysis. Each process needs funding to supply the necessary human and material resources and mitigate any hazards. Obviously, a lack of cash might result in a business's failure to adopt BD [144]. Financial support is another organizational aspect critical to the acquisition of a system, payment incentives, infrastructure security, and the procurement of equipment, which is true for H5. A crucial significance level was determined using the quantitative analysis results. As such, it is supported. This demonstrates the need to consider financial support while achieving ERMs adoption, as indicated by [145,146].

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

The current study's research indicates no evidence to demonstrate the influence of adoption costs on e-commerce use. In comparison, cost continues to be a significant obstacle to technological adoption in the literature [147]. The findings indicate that the cost of adoption has a negligible effect on the use of e-commerce. The idea behind the statement is that the cost of human capital (e.g., training and development), the cost of reengineering the company's structure, and the cost of manufacturing production line failure all contribute to the total cost [148], training the process of agility. Continuous learning enables individuals to enthusiastically share information with others in the business. The healthcare organization requires formal training for all staff in order to continue the company's development. They observed that continual training enables people to acquire new skills necessary to perform their jobs [149]. According to authors in [17], a corporation with higher-quality people resources, such as improved education or training, will have a stronger potential to innovate. Training is a critical aspect of the success of IT implementations, as shown in the literature [150]. The current study develops the following hypothesis.

Hypothesis 6 (H6). *Training has a positive effect on big data readiness in the healthcare sector.*

3.3. Environmental Context

Environmental variables are those that organizations may contact when they operate outside of their internal bounds [122,151]. Within the environmental setting, businesses are often more vulnerable to the external ecosystem's dynamic nature. Thus, the TOE model identifies competitive pressure, external support, and government laws as external factors influencing SMEs' adoption of BDA. According to Chen's [131] definition, competitive pressure refers to "influences from the external environment that cause a business to employ BDA". It refers to the pressure exerted on a business by its customers, suppliers, and rivals. Authors in [152] and Asia and Rahim [80] stated that the more businesses face competition, the newer technology is predicted to be effectively implemented. According to a review by [153], the competition had a major impact on technology adoption in SMEs in five out of ten studies they performed. According to [154], environmental constraints imposed by the media, rivals, and consumers substantially impact sustainable manufacturing practices in Egyptian SMEs, whereas environmental legislation has no such effect. According to some researchers, the rising use of BDA by rivals may push owners and managers to collect business intelligence and analytics successfully and professionally in order to maintain the firm's competitive position in the market [155].

Additionally, Chang et al. [97,156] discovered that government regulations benefit hospitals attempting to implement new information technology. As discussed before, the environmental dimension is comprised of two variables: government policy and perceived industry pressure. Each of these two factors was quantified using the Premkumar [157] research, respectively. Considering the previous considerations, as a result, this study makes the following hypotheses.

Hypothesis 7 (H7). *Government IT policies have a positive effect on big data readiness in the healthcare sector.*

The environmental government laws and legislations can be classified into two categories: regulatory and competitive. The regulatory environment's support is critical for innovation uptake [158]. Government rules and laws have been identified as significant drivers affecting the adoption of novel technologies such as cloud-based enterprise resource planning (ERP), particularly in developing nations [159]. According to Li [160], an organization is more likely to embrace new technology if the government has a clear responsibility to do so. Compliance with data, energy, and environmental requirements are additional challenges that cloud-based ERP confronts, and there is insufficient legislation to address them [161]. Thus, favorable regulatory regimes contribute favorably to the introduction and uptake of information technology [131]. Based on the foregoing data, the following hypothesis is advanced:

Hypothesis 8 (H8). *Government lows and legislations have a positive effect on big data readiness in the healthcare sector.*

3.4. BD Readiness in Healthcare Sectors

The term "technology readiness" refers to customers' proclivity towards utilizing new technologies to accomplish their aims [71]. Additionally, technological preparedness may be defined as an open mentality that accepts even the most insurmountable difficulties [29]. In other words, the more service-ready an organization or individual is, the more likely they are to accept new services and technology. As a result of past research, this study established the following assumptions on service readiness and intention to adopt [71,162]. All these factors contribute to an enterprise's technical preparedness. As a result, businesses with a greater level of technological preparedness will be better equipped to utilize cloud computing technologies [80].

Hypothesis 9 (H9). *Big data readiness in the healthcare sector has a positive effect on the intention to adopt big data.*

4. Methodology

The testing factors must be calculated to verify the research hypothesis. Designing the survey tool and having it validated by academic experts are both parts of the quantitative analysis process. The instrument was used to gather data in this analysis, which was then analyzed using partial least square structural equation modeling (PLS-SEM). A complete flowchart of adopted research design is illustrated in Figure 3.

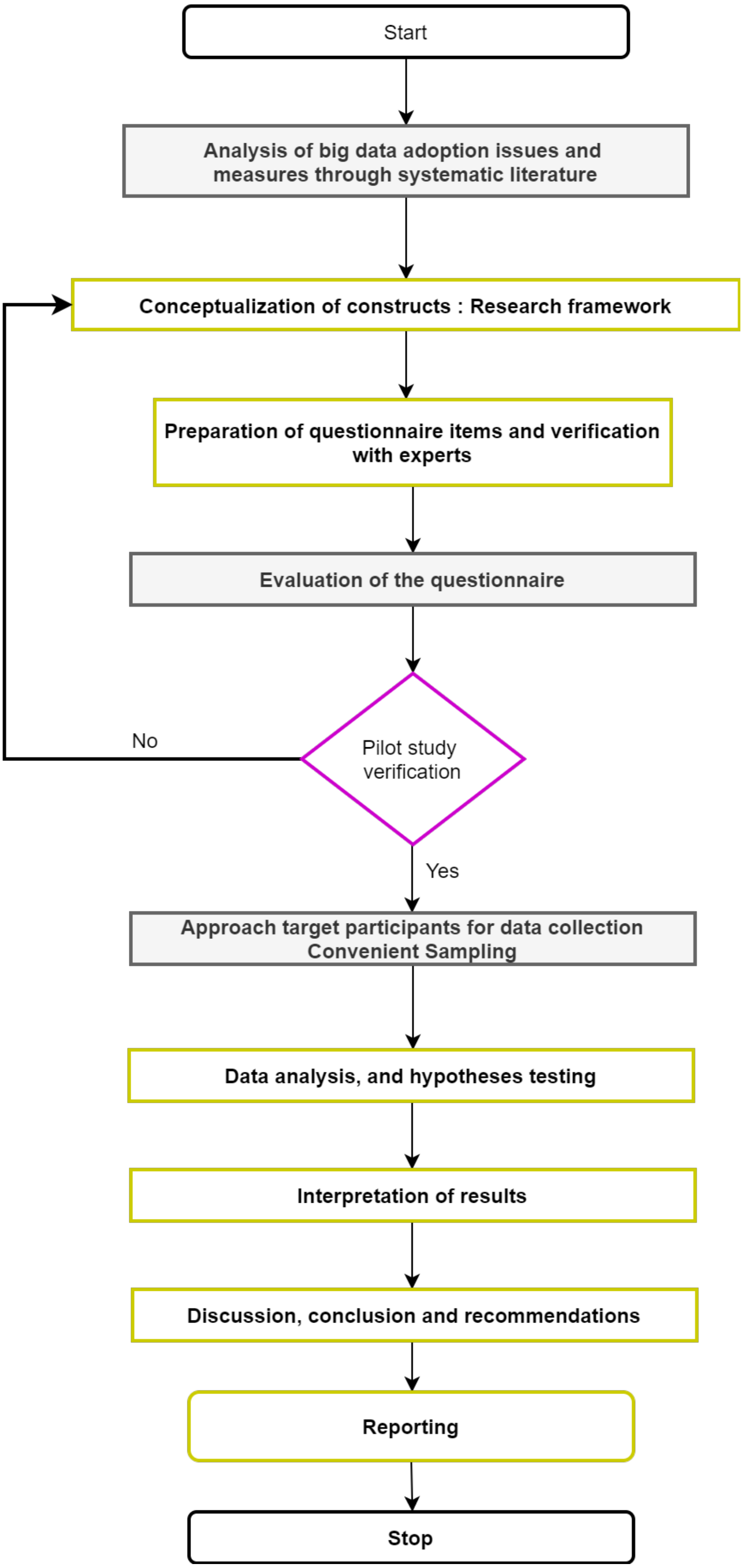

Figure 3. A step-by-step research chart.

4.1. Instrument Design

This study's instrument is divided into two sections: (a) demographic characteristics and (b) elements that will be used to calculate the autonomous, moderating, and dependent variables. Previous experiments were used to create the pieces [69,157,163,164]. The statements were graded on a five-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5); a complete sample of survey instrument is presented in Appendix A. Demographic details of the respondents are presented in Table 2.

Table 2. Respondents' demography.

Demographic Variable	Categories	Frequency (n = 254)	Percentage (%)
Age (range in years)	20–30	103	35
	31–40	92	30
	41–50	67	22
	51–60	41	13
Education	Undergraduate	173	58
	Graduate	130	42
Sector	Public	187	62
	Private	116	38
Position	Doctor/Nurse	100	33
	IT Staff	203	67
Years of experience	1–5	122	45
	6–15	93	28
	16–25	42	12
	26–35	46	15
Information Technology Competence	Low	132	44
	High	171	56
Daily usage of computers (hours)	4–7	93	30
	8–11	164	55
	More than 11	46	15
Awareness of Technology	Not aware	49	16
	Somewhat aware	68	23
	Very much aware	186	61

4.2. Pre-Testing

We evaluated our survey instrument before data collection with two main pre-testing techniques. We used two phases validation of survey design: one is content validity, and the other is construct validity, shown in Table 3.

4.3. Sampling and Data Collection Procedure

A convenient sampling method was used to collect the data. There are two types of sampling techniques available in the statistics literature: (1) probability sampling and (2) non-probability sampling. Due to the COVID-19 outbreak, it was challenging to collect data through probability sampling. Therefore, we selected convenient sampling. Convenient sampling is further divided into quota sampling and judgment sampling. As our research evaluated the significant data readiness among health professionals, we need criteria to select the proper audience. Defining the criteria and data collection comes under the judgment sampling. The following are the main criteria for audience selection.

- Participants must be health professionals.
- Participants should be a frequent user of technology.
- Participants must have some awareness about emerging technologies used in healthcare.

Table 3. Survey instrument pre-testing recommended guidelines.

Criterion	Acceptable Threshold Values
Reliability	For this survey questionnaire, two reliability criteria were followed. ➢ Cronbach's Alpha ○ Alpha ≥ 0.7(Acceptable) Alpha ≥ 0.8 (Good) Alpha ≥ 0.9 (Excellent) [164] ➢ Composite reliability ○ Composite reliability CR ≥ 0.8 (Accept) [165]
Content validity	The validity of content relates to how effectively the construct's domain content is captured by its indicators [165]. The thorough examination demonstrates how closely an individual item represents the concept being assessed [166].
Construct validity	The construct validity defined as the degree to which a test assesses what it claims to measure. Construct validity also refers to the degree to which test findings are used to identify the link between measurement items and the constructs in question. ➢ Exploratory factor analysis (EFA) ○ Factor loading ≥ 0.5 ➢ Confirmatory factor analysis (CFA) ○ Factor loading ≥ 0.6

Literature suggests that when using non-probability sampling, one must use the G-Power software to finalize the data set's upper limit. Therefore, the researcher took a G-power test for the assessment of minimum dataset selection. According to [166], to calculate the minimum limit of sample size, the researcher must incorporate the research model independent variables or the maximum number of arrows pointing at a construct. For this study, the maximum number of arrows pointing at a construct is 8. The alpha value of 0.05, the power of 0.80, and the medium effect size (f^2 = 0.15) were used in the test. In most social science research, 80% is regarded as the minimum appropriate value [166,167]. The G-power suggested minimum dataset should be 102. As [168] suggested, SEM is a large dataset technique, so the minimum number of participants should be above 200. Based on the above criteria and literature arguments, we have selected the respondents and collected the data from 50 Malaysian hospitals. In total, 550 questionnaires were distributed among healthcare professionals. Three hundred and sixteen respondents were responded, and a total 302 usable responses were incorporated for final data analysis.

4.4. Measurement Scale

The study of Malaysian public and private healthcare was done using a basic nan prosperity sampling methodology. In this context, a questionnaire was adapted and measured on a five-point Likert scale ranging from "1" to "5". The goal of this study is to construct a model that will help organizations in Malaysia, a developing country, understand the linkages between technology, organization, and environmental (TOE) settings, BD readiness in healthcare sectors, and intention to use BD in healthcare [10].

5. Results

The study utilized partial least squares (PLS), SmartPLS version 3.0., like the authors in [169], as a statistical tool to investigate the structure and measurement model since it does not require the assumption of normality because data collected through survey instruments are rarely normal [170]. Because the data were acquired from a single source, researchers assessed the risk of common method biases by analyzing the data's full collinearity, as suggested by [171] and [172]. All variables were regressed against a common variable in the full collinearity test, which states that if the VIF values were less than 3.3, there is no bias from the single source data collection. The analysis showed that all VIF values are less than 3.3. Therefore, single-source business is not a serious problem in our data. Table 4 presented the results of full collinearity test.

Table 4. Full collinearity test results.

CX	CT	TMS	FS	TR	GITP	GLAL	BDR	IABD
1.651	1.721	2.021	2.032	1.652	1.451	2.011	1.687	1.623

5.1. Measurement Framework

The partial least squares (PLS) algorithm was used to measure the model through SmartPLS. Two types of validities (convergent and discriminant) were used for measurement model assessment.

5.1.1. Convergent Validity

The measurement model was first evaluated in terms of factor loading, construct reliability, and validity. Table 4 contains the obtained values for all constructs. All indicators should have values that are greater than or equal to the respective threshold value. Internal consistency is measured by composite reliability (CR), which should be higher than the minimum threshold value of 0.70 [173]. The value of the average variance extracted (AVE) for any construct that is more than 0.05 demonstrates the construct's appropriateness [174]. The internal consistency was assessed using composite reliabilities. All constructs have reliability coefficients greater than 0.70, indicating that they are reliable for their contextual measures. Table 5 further shows that all constructs have AVE values more than 0.5, indicating sufficient convergent validity.

Table 5. Convergent validity.

Constructs	Items	Reliability			
		Cronbach's Alpha	rho_A	CR	AVE
Complexity (CX)					
BD allows me to manage business operations in an efficient way.	CX1	0.883	0.884	0.985	0.751
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	0.894	0.898	0.952	0.665
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				
Optimism (OP)					
New technologies contribute to a better quality of life.	OP1	0.882	0.898	0.892	0.663
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				

Table 5. *Cont.*

Constructs	Items	Reliability			
		Cronbach's Alpha	**rho_A**	**CR**	**AVE**
Top Management support (TMS)					
Top management supports plans to adopt the big data.	TMS1	0.872	0.873	0.982	0.712
Top management will support the implementation of BD adoption.	TMS2				
Top management support is important to provide the resources for the company to adopt big data.	TMS3				
The healthcare management is willing to take risks (financial and organizational) involved in the adoption of big data.	TMS4				
The firm size compatible with the adoption of big data.	TMS5				
Financial support (FS)					
Financial support is important for purchasing new technology equipment.	FS1	0.868	0.869	0.852	0.689
Financial support for the BD technology will strengthen the current system infrastructure in healthcare.	FS1				
Financial support will help to better secure the patient's data.	FS1				
My company has the financial resources to purchase the hardware and software required for technologies.	FS4				
Training (TR)					
Training on the BD usage is meeting my requirements.	TR1	0.860	0.862	0.971	0.721
Training on BD usage ensures that employees have received the appropriate training.	TR2				
Training on BD usage is adequate for all involved staff.	TR3				
All users have been trained in basic technology skills in the healthcare system.	TR4				
Government IT policies (GITP)					
Government IT policy can attract more foreign investors to invest in sustainable businesses.	GITP1	0.750	0.750	0.902	0.753
Government IT policy can encourage sustainable technology usage.	GITP2				
Government IT policy can improve sustainable technology efficiency.	GITP3				
Government IT policy can educate sustainable technology in Malaysian on the benefits of sustainable technology.	GITP4				
There is a lack of security rules, IT policies, and privacy laws.	GITP5				
Government lows and legislations (GLAL)					
The laws and regulation that exist nowadays are sufficient to protect the use of big data.	GLAL1	0.829	0.829	0.895	0.663
The government drives the use of the BD through incentive programs.	GLAL2				
The company requires maintaining the regulatory environment in the use of big data.	GLAL3				
The laws and regulations of the government support BD initiatives and implementation.	GLAL4				
Government laws and regulations can provide a better process for adopting technologies.	GLAL5				

Table 5. *Cont.*

Constructs	Items	Reliability			
		Cronbach's Alpha	rho_A	CR	AVE
BD Readiness (BDR) in Healthcare Sector					
The healthcare management understands how they can be used in the healthcare sector.	BDR1	0.901	0.895	0.965	0.669
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.	ITABD 1	0.925	0.882	0.856	0.603
BD technology adoption will increase the performance and effectiveness of healthcare.	ITABD 2				
I would use BD technology adoption to gather health data.	ITABD 3				
I would use the services provided by use BD technology adoption.	ITABD 4				
I would not hesitate to provide information for use BD technology adoption	ITABD 5				

5.1.2. Discriminant Validity

The statistical and theoretical distinctions between each pair of constructs are reflected in discriminant validity [174]. It is critical to make an appropriate assessment because each construct should capture a phenomenon uniquely from empirical characteristics [174]. To measure discriminant validity, heterotrait–monotrait (HTMT) was applied. As the literature suggested, HTMT is more precise than the other criteria [174]. Table 5 shows that all constructs fulfill the threshold limit for discriminant validity. The authors of [174] stated that the HTMT value should not exceed 0.85. Likewise, all the constructs have less HTMT value than 0.90, demonstrating that all constructs are discriminately valid for further analysis. All constructs' HTMT values are shown in Table 6.

Table 6. Discriminant validity (HTMT).

Latent Construct	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CX (1)	–									
CT (2)	0.451	–								
OP (3)	0.612	0.554	–							
TMS (4)	0.621	0.412	0.289	–						
FS (5)	0.355	0.423	0.287	0.521	–					
TR (6)	0.451	0.414	0.356	0.321	0.561	–				
GITP (7)	0.321	0.208	0.206	0.572	0.451	0.486	–			
GLAL (8)	0.257	0.209	0.258	0.365	0.254	0.425	0.210	–		
BDR (9)	0.265	0.207	0.236	0.211	0.361	0.352	0.325	0.321	–	
IABD (10)	0.268	0.298	0.354	0.203	0.262	0.261	0.421	0.321	0.220	–

5.2. Structural Model Assessment

In this research study, hypotheses are analyzed using Smart-PLS 3. According to [174], the basic acceptance or rejection criteria based on the values of path coefficients, confidence intervals, and matching *t*-value via a bootstrapping technique with a resample of 5000 are used in hypothesis testing [175]. Furthermore, based on [176], criticism that *p*-values are not a good criterion for assessing the significance of a hypothesis, it was suggested to utilize a combination of criteria such as confidence intervals, path coefficients, and effect sizes. As [177] presented, a hypothesis should be accepted if *p* values are significant at 0.001 to 0.005, t values are greater than 1.645, and confidence interval values are in the same interval. Table 7 shows the summary of the criteria we used to test the developed hypotheses.

Table 7. Hypotheses testing results.

Hypothesis	Path	Beta-Value (n = 254)	*t*-Value Deviation	*p*-Value	f^2	Result
H1	CX ≥ BDR	0.092	0.712	1.202	0.002	Not Significant
H2	CT ≥ BDR	0.267	4.730	0.006	0.027	Significant
H3	OP ≥ BDR	0.232	3.332	0.020	0.207	Significant
H4	TMS ≥ BDR	0.657	9.763	0.000	0.231	Significant
H5	FS ≥ BDR	0.381	3.047	0.005	0.321	Significant
H6	TR ≥ BDR	0.208	3.580	0.010	1.092	Significant
H7	GITP ≥ BDR	0.312	3.415	0.021	0.321	Significant
H8	GLAI ≥ BDR	0.235	3.983	0.048	0.024	Significant
H9	BDR ≥ ITABD	0.412	4.574	0.000	2.164	Significant

According to Figure 4, analysis of data showed that the hypothesized association between CX and BDR was not supported by the beta value (0.092) by the not significant *t* values, effect size (f^2), or confidence intervals lower and upper limits (CI), which led to the rejection of H1. According to [166], the relationship between CT and BDR is supported with beta value 0.267, *t*-value 4.730, and f^2 value 0.027, which refers to a small effect size, so we accept H2a. Furthermore, the hypothesized association between OP to BDR was also found to be significant, with beta value (0.232), *t*-value (3.332), same range confidence intervals [0.238–0.489], and f^2 value 0.207, which indicated the moderate effect size; therefore, we accepted H3. Likewise, H4 was supported because of the significance of beta value (0.657), *t*-value (9.763), and f^2 value 0.231. The relationship between FS and BDR was also significant with beta coefficient value (0.381) and *t*-value (3.047) in the same range of confidence intervals, leading to the acceptance of H5.

Training (TR) to BD readiness (BDR) association was found to be significant with beta coefficient value (0.208), *t*-value (3.580), and f^2 value (1.092), so we accepted H6. Government IT policies (GITP) to BD readiness (BDR) showed a positive relationship through the significant beta values (0.312), associated *t*-value (3.415), and same confidence upper and lower limits (0.058, 0.238); therefore, we have accepted H7. The relationship between GLAI and BDR also showed a positive relationship with beta value (0.235), t value (3.983), and f^2 value (0.024), which leads to the acceptance of H8. The final relationship has a very significant beta coefficient value (0.412), a good *t*-value (4.574), the same range of confidence intervals (0.653, 0.852), and a significant effect size f^2 value (2.164), which resulted in the acceptance of H9.

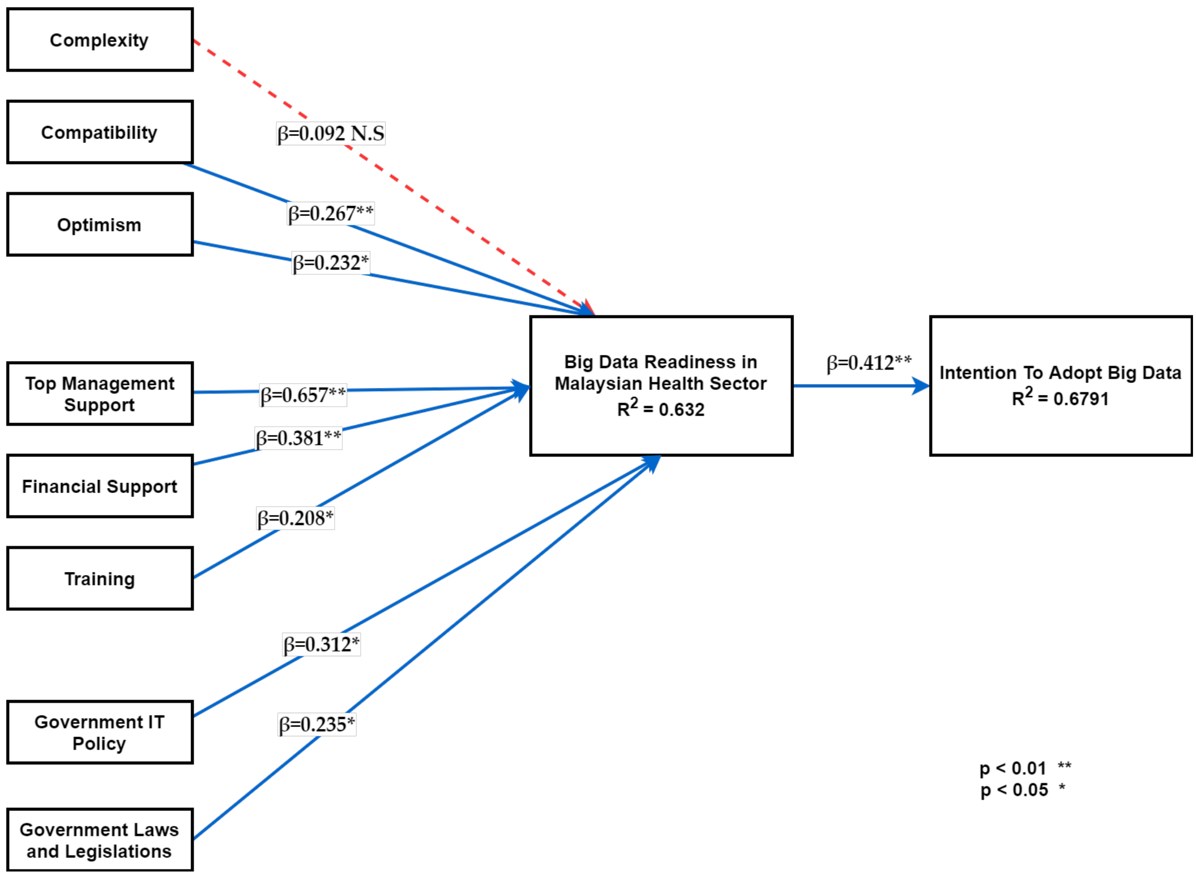

Figure 4. The PLS results.

6. Discussion

This study provided empirical literature within an information system, especially BD readiness in the healthcare sector. In addition, this study provided an assessment for BD readiness in healthcare sectors in Malaysia. This study provides a comprehensive framework that extends and contextualizes BD readiness in healthcare using three dominant factors in healthcare sectors to improve our understanding of the framework of BD in healthcare sectors. Furthermore, the results of the full-scale research will aid in developing a context-specific framework that can be exploited to examine BD continuance in healthcare sectors.

The findings provide sufficient evidence to support the notion that all TOE factors have a positive influence on employees' big data technology readiness except complexity. The TOE framework has been used to examine the influence of the technology context, where the complexity has a negative influence on BD readiness. According to the current literature [69,80,178], the complexity issues were found to be more critical in developing countries, and almost all the studies found in the literature have revealed their negative influence on BD technology readiness. Most of the previous literature showed that complexity difficulties are more prevalent in developing countries, and simplicity of use promotes developing countries to adopt new technology/innovation [83,123]. Therefore, compatibility with its technical characteristics significantly influenced BD technology readiness in the healthcare sector [123].

Optimism exemplifies technological facilities' inducers; they induce people to embrace new technologies. On the other hand, discomfort and insecurity work as inhibitors; they demotivate or postpone new technologies' embracement. Even though they coexist inside us, the inducing and inhibiting dimensions of technological facilities act separately, and each user may show different inducing or inhibiting combinations. Thus, the manager should learn and improve the TR of users as public customers to gain technology adoption successfully in an organization. This finding is in line with the technology adoption literature suggesting that complexity and optimism factors improve overall healthcare organizational performance [179]. The data analysis revealed that technological context factors significantly influence the adoption of healthcare. Moreover, they will play a valuable role in extending the healthcare literature on BD with empirical evidence. Additionally, the study will form the basis of a final framework that big data be applied to examine big data readiness with other novel technologies' adoption within the sphere of healthcare, as well as in other sectors. Lastly, the study is expected to contribute to developing the literature in the best-available organization-level framework for healthcare sector settings, as well as other similar domains. Finally, the authors in [71] utilized the TOE model to confirm that complexity and top optimism have a positive effect on acceptance, while complexity has a negative effect [71,124,179].

Top management support organizational factors have a significant effect on the adoption of BD. Some pitfalls interrupt the benefits and usefulness of BD [100]. Financial support is a key factor in the dimension of organizational context. The results revealed that all organizational factors are crucial for the adoption of big data [100,144]. If enterprises aim to benefit from BD, they should implement a series of processes that include data acquisition, storage, transmission, and analysis. Each process requires funds to provide the required human and material resources and to address possible risks. A lack of funds could obviously lead to the failure of the business adoption of big data. The significance of big data does not lie in the accumulation of data but rather in the insight into the value of data through data analysis. Therefore, to implement the necessary measures to adopt the BD, healthcare sectors need to strengthen their personnel training as well as acquire data talents to improve their advanced technology in real-time. Investigating and implementing the above measures can enhance the technical capacity, translate data into knowledge, and promote productivity and the bottom line. Thus, the three aspects of organizational context have been proven to be significantly impacted by big data readiness in healthcare.

Additionally, government IT policy and legalization refer to the support given by the government authority to encourage the assimilation of IT innovation by firms [69]. The impact of existing laws and regulations can be critical in the adoption of new technologies. Government regulations can encourage or discourage businesses from adopting BD. For example, legislators in the United States and the European Union member states have specific mandates to protect organizational data [124]. When the government requires businesses to comply with BD-specific standards and protocols, firms will be more willing to adopt big data.

7. Conclusions

7.1. Theoretical Implications

This study aimed to identify factors influencing the acceptability of BD ready in the healthcare industry of developing countries. To this purpose, a research model was established based on the TOE theory utilized in previous research by integrating work technology readiness and BD readiness in the healthcare industry, and the primary contributions of this empirical study are as follows. To begin, compatibility and technological optimism influenced BD preparedness, but not appropriateness. As this might be seen as a lack of consumer faith in the complementary nature of BD preparation in the healthcare sector, it is required to strengthen consumers' impression of the safety of BD ready in the healthcare sector, which will take time. Additionally, complexity, compatibility, and optimism reduce resistance to new technology readiness and adoption. Thus, the intention is to adopt BD, minimize user issues, and make usage more pleasant by enhancing confidence among healthcare organizations in the Malaysian healthcare sectors. This is true for BD preparation and current ICT-related motivations for BD adoption.

Second, it was discovered that, while training and support from management had a substantial influence on BD in healthcare sectors, financial support had a large influence on BD in healthcare sectors. This is consistent with Gil's [22] findings that management training and assistance greatly influence BD in healthcare sectors. Additionally, financial support has a high impact on BD in the healthcare sector. This finding of top management supports the findings of authors in [23] and authors in [34], namely that organizations exhibit early opposition to financial support, which works as a barrier to financial support adoption. Thus, to implement big data, the interest and willingness of the organization's decision-makers are required, and the management layer's support can be obtained only if the desire and willingness are there. This demonstrated that departmental training is possible. To ensure that this process runs effectively, the BD readiness in healthcare sectors must be suited to the company compared to the BD readiness in healthcare sectors.

Fifth, using structural equation modeling, this study was able to effectively analyze the factors that influence the preparedness of BD to improve the services provided by Malaysia's healthcare sector. According to the statistical findings, the healthcare industry's preparation for BD would greatly influence the Malaysian healthcare industry. According to a current study, the authors have shown that BD preparedness is greatly driven by a willingness to adopt big data. Additionally, it demonstrates that exchanging health information within a comprehensive, integrated system powered by BD is a critical aspect of the effective adoption of healthcare systems. One must keep in mind that the purpose of introducing and using BD is not to dominate but to improve the entire patient care experience. Overall IT infrastructure expenses will be significantly reduced with the implementation of the BD since healthcare providers will no longer be obliged to keep medical information locally. They do not require anything more than a solid and consistent internet connection, ideally a dedicated leased line for additional validity.

7.2. Practical Implications

The study's findings present crucial guidance and significant consequences for healthcare providers and implementers of BD preparedness. Linking healthcare functions to necessary activities of the organization and healthcare sectors' TOE, TRI, BDR, and BD is essential. By applying BD healthcare sectors, practitioners will benefit from this method. Secondly, the study's findings show that BD preparedness healthcare industries are greatly impacted by these identifying characteristics. Additionally, this study examines the influence of intention to use big data on BD preparedness in healthcare sectors in developing nations. This study will give insights for implementers of BD healthcare sectors in developing nations and suggest solutions for decreasing employees' resistance levels. Lastly, this study gives a starting point for practitioners when implementing BD techniques to reap the benefits of innovative technology in poor nations such as Malaysia.

It was discovered that facilitating circumstances and government IT policies substantially influence the link between environmental and BD preparedness in the healthcare industry. This demonstrates that the government IT policies are suitable and contribute to an increase in the ambition to utilize big data. To increase the government's readiness to provide government IT policy, businesses must first aggressively seek policy for this service and suggest changes to relevant laws and processes. However, only government laws and regulations were shown to substantially influence the preparedness of the healthcare industry for big data. It was suggested that the extent to which the government's information technology policies exerted influence varied according to the size of the healthcare organization. Therefore, because the data were obtained from a single nation (Malaysia), significant cultural variations must be recognized, particularly those that occur between developed and developing nations and impact information system management practices and perceptions of technology adoption. To generalize and amend notions, the study framework must be expanded and sampled from several nations. Additionally, existing cultural differences may influence individuals' perceptions of some key activities associated with adopting new technologies, such as big data, and more investigation of BD may give more conclusive hypothesis testing. In this regard, while the survey instrument has an adequate level of validity and reliability, it does not capture the whole breadth of organizational culture and top management support notions, as they are wide constructs.

This study further suggests that economic qualities with an expectation of profitability had a substantial influence on BD preparedness. This corroborates [25] results. In other words, it was found that utilizing intention to adopt BD increases the expectation of higher profits more than when utilizing current BD and that this data influences the readiness of new technologies for healthcare preparation and intention to use. On the other hand, it was discovered that complexity had no discernible effect on the preparation of healthcare sectors for big data. This is consistent with Das and Teng's previous study findings [26]. It was determined that if an organization does not support the big data-driven aim to embrace dependability, BD readiness preparation expectations would be lower.

7.3. Limitations and Future Research

The authors recognize that the current study has several limitations. To begin, this study focuses on healthcare organizations in Malaysia with regards to the implementation of a BD in the healthcare sector. However, this is a quantitative study; findings of this study can be generalized to other developing countries, but still more research is required in different cultures. The second limitation of the study is that the data are cross-sectional in nature, which provides only one perspective and does not accurately represent the complex relationships. Future study may use other methods of data collection to enhance precision such as self-evaluation, peer review, diary observation, and actual internet use sampling to obtain rich data and increase the explanatory power of research findings. Furthermore, this study contributed to a better understanding of the adoption of the BD system in developing nations in particular and industrialized nations in general. Thus, future researchers may validate this framework in developed nations to boost the study's generalizability, as employee resistance to change is more severe in underdeveloped nations than in developed nations [180].

7.4. Closing Remarks

BD emerging technology, which has the potential to provide strategic, operational, and other beneficial effects, continues to have a high rate of adoption in industry-wide organizations. Due to the fact that recent information system research has focused exclusively on this technology and the impact of its adoption on organizational performance, this study proposes a research model to examine the impact of BD adoption on health organizations in Malaysia and the role of strategic agility in this relationship. Finally, there are constraints on the variables that may be used to explain the entire BD digital revolution in healthcare industries. In a future study, it is anticipated that more interesting findings will be gained by generating additional variables that more accurately reflect BD preparedness in healthcare sectors, in addition to variables derived from existing ICT research.

Author Contributions: Conceptualization, E.A.A.G. and P.D.D.D.; methodology, E.A.A.G.; software, E.A.A.G. and R.F.A., validation, E.A.A.G., A.M. and R.F.A.; formal analysis, E.A.A.G. and R.F.A.; investigation, E.A.A.G. and A.M.; data curation, E.A.A.G.; and P.D.D.D. writing—original draft preparation, E.A.A.G. and A.M.; writing—review and editing, A.M., S.M.F. and P.D.D.D.; visualization, E.A.A.G.; supervision, P.D.D.D. and S.M.F.; project administration, E.A.A.G. and P.D.D.D.; funding acquisition, S.M.F. All authors have read and agreed to the published version of the manuscript.

Funding: The authors would like to acknowledge the support of Prince Sultan University for paying the article processing charges (APC) of this publication.

Data Availability Statement: Currently, we still working in this project, and we still need to use the data for further works and analysis. However, any researcher needs the data for further investigations can contact the corresponding author via email.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Sample of Survey.

Constructs	Items	References
Complexity (CX)		
BD allows me to manage business operations in an efficient way.	CX1	[69,100,130,151,163,181–183]
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	[69,71,91,100,130,181–183]
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	
Optimism (OP)		
New technologies contribute to a better quality of life.	OP1	[139,179,184–186]
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	
Top Management support (TMS)		
Top management supports plans to adopt the big data.	TMS1	[69,100,130,187–190]
Top management will support the implementation of BD adoption.	TMS2	
Top management support is important to provide the resources for the company to adopt big data.	TMS3	
The healthcare management is willing to take risks (financial and organizational) involved in the adoption of big data.	TMS4	
The firm size compatible with the adoption of big data.	TMS5	
Financial support (FS)		
Financial support is important for purchasing new technology equipment.	FS1	[191–193]
Financial support for the BD technology will strengthen the current system infrastructure in healthcare.	FS1	
Financial support will help to better secure the patient's data.	FS1	
My company has the financial resources to purchase the hardware and software required for technologies.	FS4	
Training (TR)		
Training on the BD usage is meeting my requirements.	TR1	[194]
Training on BD usage ensures that employees have received the appropriate training.	TR2	
Training on BD usage is adequate for all involved staff.	TR3	
All users have been trained in basic technology skills in the healthcare system.	TR4	

Table A1. *Cont.*

Constructs	Items	References
Government IT policies (GITP)		[71,100,130,151,190,195,196]
Government IT policy can attract more foreign investors to invest in sustainable businesses.	GITP1	
Government IT policy can encourage sustainable technology usage.	GITP2	
Government IT policy can improve sustainable technology efficiency.	GITP3	
Government IT policy can educate sustainable technology in Malaysian on the benefits of sustainable technology.	GITP4	
There is a lack of security rules, IT policies, and privacy laws.	GITP5	
Government lows and legislations (GLAL)		[197–199]
The laws and regulation that exist nowadays are sufficient to protect the use of big data.	GLAL1	
The government drives the use of the BD through incentive programs.	GLAL2	
The company requires maintaining the regulatory environment in the use of big data.	GLAL3	
The laws and regulations of the government support BD initiatives and implementation.	GLAL4	
Government laws and regulations can provide a better process for adopting technologies.	GLAL5	
BD Readiness (BDR) in Healthcare Sector		[69,71,199–201]
The healthcare management understands how they can be used in the healthcare sector.	BDR1	
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)		[71,197,199–201]
BD adoption is effective to enhance the behavioral intentions to use the BD analytics system in healthcare.	ITABD 1	
BD technology adoption will increase the performance and effectiveness of healthcare.	ITABD 2	
I would use BD technology adoption to gather health data.	ITABD 3	
I would use the services provided by use BD technology adoption.	ITABD 4	
I would not hesitate to provide information for use BD technology adoption	ITABD 5	

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