Framework For Selecting Analytics Tools To Improve Health Care Big Data Usefulness in India

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Abstract:
In the developing countries like India, there are certain challenges exist related to; how to build network between the patients, daignosis and medical personnel and including these how big data are being generated. The challenges include the relationship and interaction that exist between the big data within the various networks. Some of the challenges are like inaccuracy of data, inconsistency, and incompleteness of information and lack of confidence. The main problem arises is the inability to select the most appropriate analytics tools for the big data analysis in health sector. The objective of the current study was to provide best solution that can be used to solve the challenges of selecting analytical tools, to enhance big data interpretation which will improve the health care services in developing countries like India. For the study literarature of last 10 years of publication in the areas of big data, big data analytics of health care are collected. The data were analysed within the inerpretivist paradigm. From the analysis it was found that there are various factors which influence the big data and different tools were also analysed, the result formed a based on which a solution to solve dig data analytics problem. The solution contributes to information system and technologies in health sector. The conclusion of the study are; there exist a relationshoip between factors and the factors interaction in the process of providing medical services contribute to the souces of big data. Therefore, it is necessary to holistically analyse the bigdata from both technical and non-technical prespectives.

Keywords: Big data, big data analytics, big data usefulness, India, health care

Introduction

Information and communication technology (ICT) is a platform for all the technological activities, such as the transmission of important data, which makes it necessary to briefly discuss it prior to focussing on big data (Yu, Lin & Liao 2017). Also ICT offers certain tools and technologies that ultimately improvew the quality of healthcare facilities (Busagala & Kawono 2016). However, it is important to highlight that it also has some challenges even if it has multiple benefits. The use of ICT and big data for healthcare improvement has encountered challenges regarding integration and the unavailability of sufficient infrastructure to maximise the benefits of big data (Abouzahra et al. 2011). Big data refers to data sets which are obtained from different related or unrelated resources and are characterized by volume, velocity, and variety also known as three V's (Gandomi & Haider 2015). Deemed healthcare to the prime example of how the three V's are essential aspect of the data it produces. Big data are known to create value. However, that can only happen once it is analysed using data analytics tools. According to Elgendy and Elragal (2014), simply the meaning of big data analytics is that it is the application of analytics techniques on big data. In addition to the three V's, the science of big data focuses on heterogeneity, which includes levels of unfiltered data, media format and complexity (Nanni et al. 2015). In an attempt to explore the value and usefulness of big data, heterogenity poses a challenge in its analysis (Jagadish et al. 2014). Heterogenity of the types of devices used and the nature of data generated are risks associated with big data (Marjani et al. 2017). Labrinidis and Jagadish (2012) argued that heterogenity hinders progress in the creation of value from data, therefore it can be said that heterogenity is being the important factor for big data analytics, especially in the case of integration (Micheni 2005).

The objective of the study was to find out the factors that influence the use of big data analtics to improve healthcare service delivery in Indian environment. To meet this objective, it is important to understand the factors that influence data analytics from human point of view and a big data perspective. From the data analysis using the hermeneutics approach, various factors that influence big data are being find out.

This research paper is divided into eight sections that include sub-sections. After that the objective of the study is problrmatised. After that various reviews are being done related to big data analytics and health care of India as well as international perspective. In the next section, research methodology is discussed, and after that a discussion on phenomenon are being done. The proposed solution related to the framework for big data analytics are being presented. After that recommendation and finally conclusion of the research are being depicted.

Problematising the health care big data in developing countries like India

The main motivation of this study is in two fold: (1) majority of previous studies focus on the importance, challenges and oppurtunities of big data analytics (Shahbaz et al. 2019) and very few studies focus on big data of health care in developing countries (Luna et al. 2014). In many develpoing countries reliable diagnosis is becoming a challenge and often medical practitioners reorder test, which can be attributed to lagging analytics of healthcare big data.

In India and many developing countries, it is a challenge to bring patient's big data together within a facility or from different health programmes (Luna et al. 2014). This challenge is caused by lack of integration and analysis of a variety of health care big data to address related problems (Kankanhalli et al. 2016). Thus, scalability is a primary obstacle for big data analytics,as well as ontological extraction and semantic inference, to support innovative processes in the care for pateints. The analytics tools also pose challenge to both scientists and IS/IT specialists in different ways. Form the academic front, big data analytics is found to be a disruptive innovation, which is reconfiguring how research is conducted and has epistemological implications on data revolution (Kitchin 2014). Form both emperical and experimental perspectives, It was found that big data present technical challenge to analytics tools, because of its volume, variety and velocity (Priyanka et al. 2014). The relationship formed during the process of providing medical care contribution to big data. Therefore it is important to employ the most appropriate analytics tools for examing the relationship that exists between humans, that is between medical personnel and patients on the one hand and between human and non-human(data and medical apparatus in providing and receiving health care services) on the other hand. Exploring these relationships brings out the issues that can contribute to big data analytics. Gaining clarity on these issues helps in proposing a solution that would be suitable for healthcare. Most importantly, it helps to develop a solution that considers health care needs in the context of India. In that, one of the critical technical challenges of big data analytics is the lack of capability to handle large-scale transactions from non-standard medical terminology in patient records (Purkayastha et al.).

Literature Review

Big data are collected from various sources, such as health care (Song & Ryu 2015), and national geographic conditions monitoring data and earth observations data (Li Yao et al. 2014). Big data are increasingly useful to scientists, health practitioners and the society in general (Shu 2016). To improve big data usefulness for healthcare services, it requires analytics. Big data analytics refers to a collection of analytic techniques and technologies that have been specifically designed to analyse big data to inform decision making (Kwon et al.). Shahbaz et al. (2019) findout that health care organisation are lagging in the sophisticated use of big data analytics, in spite of the fact that the sector generates huge volume at high pace. Big data analytics engineer transformation data sets, from raw to refinement stages. Innovation of big data from the perspective of developing countries can be understood as all the scientific, technological and healthcare activities (Micheni 2015). Big data analytics are often considered as the process of examining large amounts of data from different sources and in different variations in order to gain an insight that can enable decision making in real or near time (Sun et al. 2013). According to Kwon et al. (2014) big data analytics are the technologies and techniques that can be employed ti analyse large scale and complex data to improve a firm's performance. However, the employment of data analytics cannot be limited to just business; other sectors have to be considered as well. Big data analytics can be further described as a means of helping dsicover valuable decisions through understanding of data patterns and their relationships using machine-learning algorithms (Archenaa et al. 2015).

Big data analytics enable the capturing of insights from the data gathered from research, clinical care settings and operational settings to build evidence for improved care delivery as stated by Namibiar et al. (2013). Some studies proven that the analysis of big data can help uncover patterns and relations in healthcare, which are often new to health specialists. Earlier studies suggested that digitising big data through the act of integrating sources within a hospital network can help with accountability within an organisation and ultimately realise its benefits. Eswari et al. (2015) reveal that the analysis of big data not only helps in finding out patterns but also helps in predicting outcomes. Data analytics enable the systematic review of existing medical information and inform the efficiency of service of health professionals and facilities (Kavitha et al. 2016). From the perspective of the patients with more accurate informations that can help in decision making through the analysis of their data (Sarkar 2017). The patients also benefits from analytics, based on care that is supported by a timelier diagnosis, as well as a more appropriate medications (Sakar et al. 2016). Non-technical factors, such as resistance to change from employees, which manifest from lack of training and understanding are a key challenge affecting big data analytics, especially in developing countries (Shanbaz et al. 2019). From a technical viewpoint, the integration of multiple sources of data sets brings about the challenge of increased volumes, increased velocity and variety of data. The challenges in big data analytics as the only way to yield its value is through analysis (Sarkar 2017). The slow progress in the development of technology, which supports big data,especially in developing countries is seen to be shocking as earlier predictions stated that the applications of big data would be inevitable (Lee & Yoon 2017).

Research Methodology

A qualitative method and an interpretivist approach were employed in the study. The approach starts within the premise that people's knowledge of reality and human actions are socially constructed (Walsham 2015). The interpretivist approach was preffered as the most suitable and used in the study because of three main reasons (1) it shares a belief that the world is socially constructed and these constructions are possible only because of the human ability to associate meanings with objects, events and interactions (Prasad 2017); (2) within the interprevist approach there is no objective reality that can be discovered by researchers and replicated by others, in contrast to the assumptions of postivist science (Walsham 2015); and (3) in interpretivism, reality is individually constructed, and there are as man realties as individuals (Scotland 2012). The belief from these reasons helps to gain an understanding of the factors that influence big data analytics for healthcare services in developing countries. From an interprevist angle, existing materials, which of course comprise findinds from emperical studies, various views and opinions, were gathered and examined. Two main criteria were used in the collection of the materials: (1) the key areas of focus were big data in healthcare and healthcare challenges in developing countries, which formed the first part of the criteria; and (2) materials published within 10 years from 2013-2023 was used as the decade within which data were collected, the second part of the criteria. According to Iyamu et al. (2016), As presented in Tables, a total of 49 materials were gathered from academic databases, which include AIS, EBSCO, Google Scholar, IEEE and ProQuest. Within the context of developing countries, the use of big data in providing healthcare services is influenced by its premise, on the one hand (Luna et al. 2014). On the other hand, the use od the analytics tools manifests in some of the challenges that are experienced in providing care to patients (Li et al. 2014). Some of the existing literature in these contexts, big data and big data analytics within health care form the perspective of developing countries are briefly described in above tables.

The practice of health care heavily relies on patient's data sets in faciliting the services that practitioners provide (Mathew & Pillai 2015). This trigerred the phenomenon being studies in the areas of big data and health care as breifly described in Table 1. Table 2 provides a brief description of the disparities as well as challenges and gaps in the adoption and use of big data analytics tools for healthcare services (Purkayastha & Braa 2013). This includes the integration of health care big data and systems.

TABLE 1 : Big data and health care

Object and Focus	**Descriptions**	**References**
Scope and benefits	Based on its potential benefits, the focus has been on big data in health informatics, new epistemologies and paradigm shifts	Kitchin (2014); Kumar and Singh (2017)
	Big data are employed for a secure healthcare system, which include conceptual design and big data as an e-health service	Liu and Park (2014); Sarkar (2017)
	Increasingly, big data are employed for healthcare services, such as a divided latent class analysis for	Abarda, Bentaleb and Mharzi (2017)

	big data.	
Challenges and gaps	There are challenges in the use of the big data for health care services, which include integration,scalability and complexity of heterogenity The big data analytics are a disruptive innovation that has reshaped research focuses and challenge semantic inferences to suipport innovative activities and processes in providing care for patients	Jagadish et al. (2014); Nativi et al. (2015). Hilbert (2016); Labrinidis and Jagadish (2012).

Table 2 : Big data analytics and health care

Object and Focus	**Descriptions**	**References**
Scope and benefits	The concepts of big data analytics is gaining presence inboth academic and business domains, including government health environment Beyond the hype, promise and potential, the concept of big data analytics has been used to focus on the analysis of risks and integration of data sets within the health care envirnment	Archenaa and Mary Anita (2015); Nanni et al. (2015) Gandomi and Haider (2015); Raghupathi and Raghupathi (2014)
Challenges and gaps	Integration of systems to access healthcare big data. This is attributable to lack of architecture that is specific to healthcare big data Lack of understanding of the pros and cons of big data analytics in its adoption and use for healthcare services. This challenge is influenced by the uniqueness of health-related tasks, such as cardiovascular care.	Bare Bhakti and Kini (2017); Marjani et al. (2017) Bottles, Begoli and Worley (2014); Rumsfeld, Joynt and Maddox (2016)

Table 3: Health care in developing countries

Object and Focus	**Descriptions**	**References**
Scope and benefits	Bangladesh and Saudi Arabia are different from African countries such as Bangladesh, Saudi Arabia, South Africa, South Korea and Tanzania. In many developing countries, the use of big data analytics has been explored from various angles, such as cloud-based solution, innovation and diffusion.	Malaka and Brown (2015); Moktadir et al. (2019); Song and Ryu (2015) Belle et al. (2015); Micheni (2015); Mishra, Kalra and Choudhary (2013).

Challenges and gaps	Adoption of big data analytics tools in providing healthcare services in developing countries has been challenging, particularly in the areas of integration and cloudbased innovation	Alaboudi et al. (2016); Busagala and Kawono (2013)
	There are very few studies that focus on big data analytics for healthcare services from the perspective of developing countries. This is a gap that makes many facilities and developing countries sceptical in their attempts to adopt the concept	Abouzahra (2011); Luna et al. (2014); Malaka and Brown (2015);

From the perspective of developing countries a brief description of the benefits and challenges of big data analytics in health care that are described in literature are provided in Table 3. Apparently the use of big data analytics for health care services in India has become synonymous with numerous problems, challenges, obstacles and pitfalls, which has prompted studies, such as those that are presented in Table 3. In the analysis of data, the hermeneutics approach was followed because it aims to unviel the concealed messages in the text through ssubjective reasoning (Kalaga 2015). The approach was employed by reading through each of the data sets (literature), forward and backward and in circle. This helps to gain better understanding and to reference particular culture and historical time (Schmidt 2016). The approach was thus useful in identifying the factors that influence big data analytics for healthcare services, which focuses on developing countries. Another importance factor is that, from a hermeneutics perspective, human meanings are often not expressed directly but are embedded in artefacts by their creators and it can be known through interpreting these artefacts. To gain an underastanding of the meaning in the data, a close relationship with the text was required, hence the forward and backward approach. In summary, the hermeneutics explores how people read, understand and handle texts within contexts.

Discussion of analytics tools

Big data analytics are used as a solution for healthcare systems in many countries including developing countries (Song & Ryu 2015). The four most common types of data analytics tools are predective, prescriptive, descriptive and diagnostic (Shao et al. 2014). In the context of healthcare, Raghupathi et al. (2014) argued that predictive analytics are used to anticipate risk through analysis of historical health data and patterns. According to Rumsfeld et al. (2016), prescriptive analytics are used to support medical decisions on individual cases by assessing the risk and benefits of the available solutions. The descriptive analytics provide a summary of the past and the present data, which can be used to inform health care decisions (Mathew et al. 2015), while the daignostics analytics focus on findig solutions or answers as to why certain occurences happen the way they do (Shao et al. 2014).

In the context of healthcare, big data analytics can be used to solve the complexities that reside within information systems that are used to host and manage patient's data sets (Bare Bhakti et al. 2017). Mancini (2014) explained how to use of analytics has the potential for enhancing the provisions of quality treatment, better surveying of public health, as well as improving responces to and mitigation against disease that may affect patients. in spite of these identified challenges, the use of analytics for patients data is not a one-way affair and it has its own challenges as well. In healthcare, lack of integration is listed as a challenges as brought on by different types and sources of data sets (Abouzahra

2011). However, there are no specific challenges that are of a standard type. In most developing countries, there are often different types of challenges and hence, unique solutions are relatively required (Alaboudi et al. 2016).

Other challenges of big data analytics include creating efficient and strong analytics methods that are essentials for health care services (Peek et al. 2014). According to Kumar and Singh (2017), the challenges start from the choice of big data analysis platforms and the functionalities in terms of criteria such as scalability. The integration of big data analytics with current healthcare processes and practices is another challenge, which has been highlighted by Lee and Yoon (2017), in that it is not easy to get them to co-exist and function appropriately within health facilities. The traditional systems no longer suffice for big data as stated by Bare Bhakti (2017) and this has resulted in issues sucha as the inablitity to conduct decision-making in real time, which ultimately challenges predictive analytics. The challenges in big data analytics limit the potential of health care big data in providing services. This is because the analytics tool seems to be the only way to maximise value and usefulness from patient's big data through its use for analysis (Sarkar 2017).

The outcomes from the analytics tools lie in their applications (Priyanka et al. 2014). This makes selection and use of the analytics critical, if it is to help in addressing functions such as clinical decisions support, personalisation of health care activities, public health, and operationalisation of processes and policies implementation. The criticality of these functions makes it even more crucial to be more detailed in assessing the existing systems, because majority of them focus on the same or similar solutions, which include to store, find, analyse, visualise and secure data sets. Some of the most common analytics tools are MapReduce, Hadoop, STROM, Tableau, Apahe Hadoop (Chang et al. 2016). Although the existing solutions seem to hold promise, health care big data still encounter challenges (Rumsfeld et al. 2016).

Heterogeneity extends to network within which big data exist. According to Law (1992), networks are materially heterogeneous. Agents, texts and devices that are subsequently generated form part of the network. It became crucial in examining relationships in which actors participate and influence the shape of the heterogeneous networks (Dwairtama et al. 2014). Heterogeneous entities such as people and data contribute to forming networks (Horowitz 2011). Materials join together to generate data and reproduce themselves (Law 1992). Examples of reproduction of bog data include: digital closed-circuit televisions (CCTV), recoding of retail purchases and health care historical records (Micheni 2015).

In the course of health activities, the networks become heterogeneous, which also increase the levels of security, making it more difficult for tools to produce useful and purposeful data sets from the analysis (Archenaa et al. 2015). In addition, the heterogeneity of data imposes new requirements from source viewpoint which can also be challenging as the practitioners attempts to trace the origins.

Big data analytics framework

Following the nermeneutics approach, integration, structure, skill, availability of data, requirement, data sets, appropriation apparatus, external organisation, integrity and translation were identified as the main entities that influence the usefulness of healthcare big data for service delivery. The identification of the factors results from two primary qualifications: (1) the frequency of each factor, which was based on the number of articles that the factors has appeared in at the time of this study; and (2) which of the factors co-occur. As shown in Figure 1, the actors are influenced by the types and sources of big data, classified as networks. Based on the networks, analytics tools can be appropriately selected, aimed at enhancing the usefulness of healthcare big data. The actors, networks and tools are grouped into categories (levels) A, B and C repectively which together form the framework as shown in Figure 1.

The framework is proposed as a solution, which can be used in addressing the challenge of big data, towards improving health care services delivery in a health facility. The framework is a bottom-up approach. This means that from the actors (A1 and A2), data are generated and grouped into categories of networks based on the networks; analytics tools and selected and applied. The first level, Level A consists of the main factors that influence the usefulness of the healthcare big data. The factors are divided into two parts: A1 (technical) and A2 (non-technical). This level is intented to aaist health care practitioners to gain knowledge and an understanding of the importance of: (1) factors og influence and (2) hopw the factors are interrelated or interconnected. Level B hekps to identify, examine and understand the networks, which consist of historical records, diagnoses, results and medications. This level enables identifiation of the factors that influence the selection of tools as well as the analysis od patients' big data. The last level, Level C, comprises analytics tools, from which selection can be made for health care big data analysis. The discussion that follows should be read within the framework (Figure 1), to gain a better understanding about the framework and how it can posible be applied.

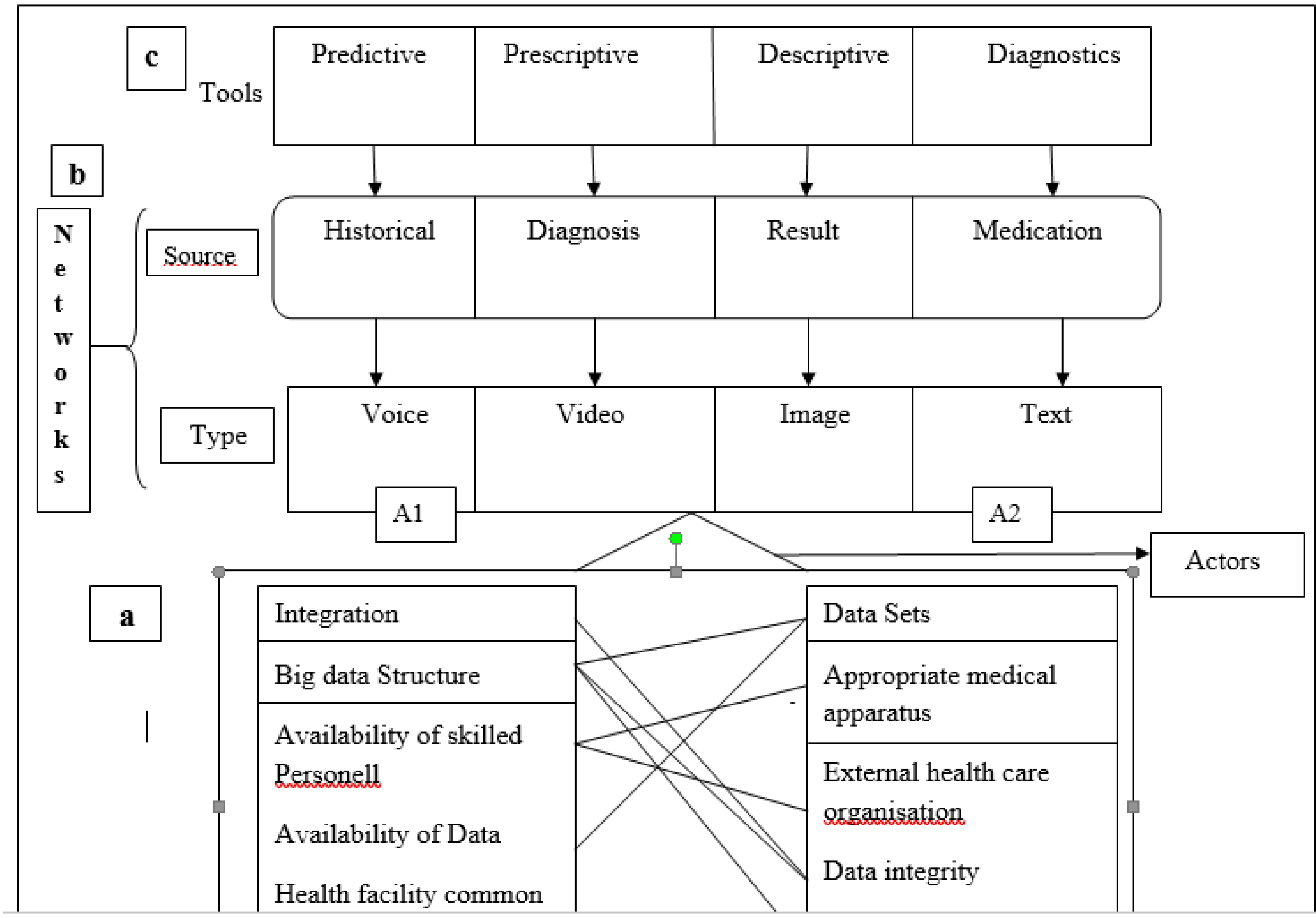

Figure 1: Big Data analysis Framework

Influencing Factors (Level A)

The factors that influence big data anallytics for health care services are revealed in Level A of figure 1. The factors are classified as actors. In this study, actors are anything that has the ability to make a difference (Callpm 1986). The factors were grouped into two categories, A1 and A2, which are data

Science/IT (Technical) and health facilities (Non-technical) respectively. The influencing factors are both human and non-human actors because each of them has the ability to make a difference. The factors in the A1 were mapped against those in A2. This was purposely done to establish the relationship between factors and begin to understand how they directly or indirectly influence the healthcare service delivery. By indication, this means that the factors influence both healthcare practitioners and the IT unit, which draws their relationship and necessitates alignment between the units. On the one hand, the health practitioners solicit for support from the IT unit to enable their activities. On the other hand, the unit requires information through interaction in order to provide support and enable the processes and activities concerning healthcare.

The mapping helps in that many medical practitioner often limited in terms of the insight they can gain from the classification of patient's big data, which guides their analysis of the data sets towards providing services. Currently ,as revealed from this study, many medical practitioners continue to employ traditional methods are time-consuming, are less effective and produce less accurate results, which significantly contribute to facility in India. The existence of these factors holds both negative and positive connotations and effects. This is primarily because each of the factors has the capability to make a difference of either enabling or constraining the use og big data in providing health care services. However, through acknowledging these influencing factors, they could drive health facilities towards proper selection and use of big data nanlytics tools. As presented in Figure 1, the influencing factors can potentially support and enable the health facilities towards many benefits through the following three main ways: (1) Put the types of data into perspective, (2) Shape their sources of data and (3) Select the most suitable data analytics tool.

With due consideration to these influencing factors, health facilties would be able to identify the types of data they accumulate daily and help put them into perspective. This way health facilities would be able to identify the structured and unstructured types of data by grouping it into big data. Moreover, instead of disregarding unstructured data sets in their analysis, unstructured data sets would also have a role in patient's treatment and ultimately contribute to improving the standard of health provisions. By putting their data types into perspective health facilities would also be able to shape the data sources through which knowledge is gained. The knowledge enables traceability of the sources or origins of patients' data sets. This helps in having standards source of reference, when conducting health activities which lead to analysis as well as providing care to patient's health conditions. Knowledge about data types and sourceswould be useful to advise health facilities on the suitability of analytics tools choice. Thus, decision can be substaintiated in that data types and their sources are known and traceable. This assists in formulating requirements and provides clarity in the selection and use of big data analytics tools for health care big data in order to improve service delivery.

Networks (Level B)

As shown in the framework (Figure 1), there are two main categories of networks namely (1) Source of the data. (2) Type of data.

Source of data

The sources of big data witin healthcare facilities are a part of the different networks that exist in the environment (Iyamu & Mgudlwa 2018). From the perspective of healthcare facilities, each source of patient's big data consists of actors with aligned interests. The source of big data as proposed in the framework includes historical data, diagnoses, results and medication. Each of these sources of big data has groups of interested actors for the purposes of bettering patient's care. For instance, historical data are used to inform decisions made on patient's health condition. This means that diagnosises and results from tests and medicines are based on the patient's medical history. Through analysis of each patient's medical history health practitioners are able to gain an insight on individual cases which enables better decision making.

Types of Data

Similar to other developing countries, there are also different types of data increasingly accumulated within Indian health care facilities. A group of data of the same type forms a network (Mgudlwa et al. 2018). The existing networks are voice, video, image and text data. Othera actors of each of the networks include the contributors (Patients) of the data, extractors (Medical Practitioners) of the data managers of the data, support and enablers of the data (IT/IS specialists) and those that make use of the data.

Analytics Tools (Level C)

The four most common types of data analytics tools are predictive, prescriptive, descriptive and diagnostic (Shao et al. 2014). In the context of health care, Raghupathi et al. (2014) stated that predictive analysis are used to anticipate risk through the analysis of historical health data and patterns. According to Rumsfeld et al. (2016), prescriptive ananlytics are used to support medical decisions on individual cases by accessing the risk and benefits of the available solutions. Mathew and Pillai (2015) stated that the descriptive analytics provide summary of the past and present data, which are used to inform health care decisions. Shao et al. (2014) stated that diagnostics analytics help in finding out why certain things are happening. Each of these tools has the capability of adding value to the activities of healthcare but from different perspectives. Therefore, there should be criteria for selecting the appropriateness of the tools. The choice of tools is determined by the healthcare facility need from the existing big data. By establishing what they intend to use the big data for the organisation is able to narrow down what tools is best suitable for their goals. Thus, if an inappropriate or less appropriate tool is selected, there will be risks and challenges during analysis. Thus potentially results in incorrect diagnosis, medications and counselling.

Validations of the framework

Although there exist some emperically validated artefacts, none can be used as a sole basis for research purposes as they did not focus on developing countries. This makes this study an early exploratory study in the context of developing countries. As a result, it was difficult to validate the framework because of its uniqueness, 'healthcaren big data analytics' in the context of developing countries. Thus the influencing factors were used. Although the data used in this study were based on literature, the framework was validated to ensure that the influencing factors (actors) are still applicable in the contexts of both developing countries and healthcare, this was against the existing model using the influencing factors, which include integration, structure, skill set, availability data set. Data integrity and translation This IS framework can be validated through different ways, such as through case descriptions framework or components of the framework. Belle et al. (2015) argued that validation of framework can be objective or subjective. In this study.the influencing factors were used in validating the study by employing a subjective approach.

Integration of patients' data sets, which include their risk profile, can be used to improve healthcare services (Elgendy et al. 2014). Availability of patient's big data is critical primarily for the purpose of achieving clinical predictive analytics (Bates et al. 2014). This helps to ensure ethical standardss and manage privacy concerns. Data sets are most purposeful through predictive and diagnostics analytics tools for decision making and achieving healthcare solutions. Based on the validation of this tudy is suitable for gaining a better understanding in selecting analytics tools to improve the usefulness of big data in healthcare in developing countries.

In practice

The factors revealed in this study are intended to contribute to India and other developing countries healthcare envirnment from the following angles; in the development or review of policies, rules and regulations towards addressing some of the challenges that have been encountered in healthcare over the years. In practice, the implementation of the framework requires formulations of templates for each of the levels as depicted in Figure 1.the templates should consists of critical success factors that are environment and context based this is to ensure that the implementation of the framework appropriately guides the selection and use of analytics tools making healthcare big data more useful and ultimately improving service delivery. Only then, the framework can help bridge that the gap created by lack of framework:

1. Enlightening practitioners on the factors that influence big data analytics in the Indian healthcare environment.
2. Being a step-by-step guide on factors considered prior to selecting a data analytics tool.
3. Improving the quality of services through the use of big data analytics.

In addition, prior to implemenatations of the framework, big data users (healthcare practitoners) have to be educated on the basics of big data analytics. The framework can therefore further guide them on step-by-step basis in putting that knowledge into practice.

Conclusion

This study helps to address some of the challenges that are encountered in the healthcare environment from an IS research viewpoint. A solution is proposed through a framework to provide a clearer understanding of the factors to consider prior to selecting and using big data analytics tools. This is primarily to increase the usefulness of the big data for health care services, particularly in developing countries like India. This study highlights that successful selection and implementations of big data analytics tools requires knowledge of components stated within the framework. Through the framework and the influencing factors, the study adds to academia in IS and health sciences understanding of the use and roles of big data in the Indian health care environment. In addition, the study can be of importance and benefits to the academics mainly because of its emperical nature.

This study addresses an area of big data analytics and healthcare in developing countries, which has not previously been explored. The framework can therefore be beneficially explored further in order to create artefact for validation credibility for future studies in the areas of big data analytics and health care big data in developing countries. Based on the analysis, findings and the interpreatation, further research on this study is recommended. As the framework has not yet been applied, future studies could focus on the application of this framework on a healthcare based care study. In additon, the use of different theories is encouraged.

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