AN INVESTIGATION INTO USABILITY OF BIG DATA ANALYTICS IN THE MANAGEMENT OF TYPE 2 DIABETES MELLITUS

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ABSTRACT
The global prevalence of Type 2 Diabetes Mellitus (T2DM) has been on the rise over the last four decades and is expected to rise further in the future. Big Data applications such as Artificial Intelligence (AI) and Machine learning (ML) are increasingly being used in the healthcare industry to manage various aspects of patient care. Researchers have so far studied the adoption of technologies including AI and ML in various contexts using technology adoption frameworks in the information systems (IS) domain, where the usability of technology is just viewed as one factor. Although, researches on technology adoption models in the IS domain has indicated that usability has a significant influence on the adoption of a technology, it appears that there are limited attempts made to study the factors influencing the usability of big data applications such as AI and ML for the management of T2DM. Since usability not only a factor that impacts the adoption of a technology, but also determines the outcomes of the management process, there is a need to understand the factors that influence the usability of a big data analytics application for the management of T2DM, this research aims to identify and analyse the factors influencing the usability of big data applications such as AI and ML in management of T2DM. The research is designed as mixed method research with qualitative research undertaken first to confirm the conceptualised research model followed by quantitative research to genaralise the model. This research would contribute to the academic literature in the areas of Information Systems Quality, Human-Computer Interaction (HCI), design and development big data applications, usability engineering, user experience (UX), and usability measurement model. The contributions from this research would also benefit the healthcare industry, predominantly that part of an industry that is directly involved in the management of T2DM and indirectly involved in the management of comorbidities on T2DM. The learnings from this research can also be extended to the management of many other chronic conditions and many other contexts.

KEYWORDS
Usability, Big Data Analytics, Type 2 Diabetes Mellitus (T2DM).

INTRODUCTION
Type 2 diabetes mellitus (T2DM) is the most prevalent type of diabetes and contributes to 90% of all cases of diabetes (Cho et al., 2018). According to Ogurtsova et al. (2017), the global prevalence of diabetes mellitus has increased over the last forty years and is expected to increase further in the future. International Diabetes Federation (IDF) has reported the global prevalence estimates of diabetes mellitus to be 425 million. Although, diabetes mellitus cannot be cured, WHO suggests that the condition can be managed properly to significantly improve the patient's quality of life (WHO, 2013). The comorbidities associated with diabetes mellitus have

increased significantly in the last decade due to risk factors such as lifestyle changes and changes in dietary habits (Bellou et al., 2018). As a result, the number of deaths (mortality) directly and indirectly associated with diabetes mellitus has also increased in the last decade (Desveaux, Lee, Goldstein, & Brooks, 2015; Hambleton, Bafadhel, & Russell, 2016). As there is an increase in the rate of co-morbidities and mortalities associated with diabetes mellitus, there is a dire necessity to manage the condition effectively and efficiently. The management process gets more complex when the patient's suffering from multiple co-morbidities simultaneously (Caughey, Vitry, Gilbert, & Roughead, 2008; Islam et al., 2014; WebMD, 2016). Hence, there is a need to develop a solution to ensure such complex cases of T2DM are managed efficiently and effectively.

Big data applications are being increasingly adopted in the healthcare industry to analyse, predict, prescribe and visualise data with the intention to improve the healthcare decision-making process. There is also great potential for big data analytics applications such as artificial intelligence (AI) for prescriptive decision making and machine learning (ML) for predictive decision making, in the management of chronic conditions such as T2DM to improve the effectiveness and efficiency of the management process (Leppert and Greiner, 2016, Raghupathi and Raghupathi, 2014, Stylianou and Talias, 2017). After the adoption of big data application by an organisation, the desired outcome of using the big data applications such as AI/ML could only be achieved if the applications are satisfactorily utilised by the stakeholders. Hence, the degree to which the desired outcomes are achieved will depend on the ***usability*** of the application (Bevan et al., 2015). In the management of T2DM, the primary stakeholders are the physicians, healthcare workers, dietitians, pathologists, and patients. The desired outcomes of adopting a big data application in the management of the T2DM can be achieved only if these stakeholders utilise the big data application such as AI or ML satisfactorily. The researchers in the field of usability and human-computer interaction agree the usability impacts the ability to use an application and thus impacts the organisational outcomes such as efficiency, effectiveness, and satisfaction. Given that usability of an application significantly affects the outcomes of the T2DM management process, this paper aims to develop a conceptual model to understand the impact of usability of big data applications such as AI/ML for the management of T2DM.

LITERATURE REVIEW

An in-depth literature review was undertaken to identify the latent variables and sub variables to be included in the conceptual model of usability and the context where the model would be applicable.

Why T2DM?

Diabetes mellitus is a chronic condition and has no cure. Hence management of the condition is essential to enhance the quality of life of the patients suffering from diabetes mellitus (American Diabetes Association, 1997). The American Diabetes Association has categorised diabetes mellitus into four major types – Type 1 diabetes mellitus (T1DM), Type 2 diabetes mellitus (T2DM), gestational diabetes mellitus (GDM) and Other Specific Types of Diabetes (OSTD) (American Diabetes Association, 1997). Beyond these classifications, the researchers are debating the introduction of a new taxonomy for Alzheimer’s Disease as Type 3 diabetes mellitus (T3DM) since it a neuroendocrine disorder and the characteristics of the Alzheimer’s disease is closely associated with the characteristics of both T1DM and T2DM (de la Monte and Wands, 2008). Type 2 Diabetes Mellitus (T2DM), previously known as non-insulin-dependent diabetes or adult-onset diabetes is a metabolic disorder associated with relative deficiency of insulin(Alberti and Zimmet, 1998). T2DM is the most prevalent type of diabetes, contributing to 90% of all cases of diabetes (Cho et al., 2018). Hence, this paper attempts to focus on T2DM while developing the conceptual model for usability of big data application such as AI/ML.

International Diabetes Federation (IDF) started reporting the global prevalence of diabetes mellitus from the year 2000. In 2000 IDF reported the global prevalence to be 151 million in its first edition of the Diabetes Global Atlas and this number steadily grew over the years and in its most recent (eighth) edition of the report, IDF reported the global prevalence estimates at 425 million, which translates to one in eleven adult population of the world to be diabetic (Cho et al., 2018). WHO suggests that the non-curable chronic conditions such as T2DM could be managed properly to improve the patient’s quality of life significantly (WHO, 2013). The co-morbidities associated with diabetes mellitus have increased significantly in the last decade due to risk factors such as lifestyle changes and changes in dietary habits (Bellou et al., 2018). As a result, the number of deaths (mortality) directly and indirectly associated with diabetes mellitus has also increased in the last decade (Desveaux et al., 2015, Hambleton et al., 2016). As there is an increase in the rate of co-morbidities and mortalities associated with diabetes mellitus, there is a need to manage the condition effectively and efficiently. The management process gets more complex when the patients suffer from multiple co-morbidities simultaneously (WebMD, 2016, Caughey et al., 2008, Islam et al., 2014). As there is need to develop a solution to ensure such complex cases are managed efficiently and effectively, this conceptual paper limits the context of the model to the management of T2DM.

Why India?

Shaw et al. (2010) reported that India has the largest number of people suffering from Diabetes mellitus and with approximately 51 million people (7.8% of the population) affected by the condition. The prevalence has increased to 69.19 million by 2015 and 72.94 million cases in 2017 (Cho et al., 2018). also, It is estimated that the annually on average 1.8 million new diabetes mellitus cases are being added existing cases, which also places India as a country with the highest growth rate of diabetes mellitus condition in the world(Shaw et al., 2010). The overall prevalence of diabetes mellitus in India was estimated to be 7.3% and some of the states had a prevalence rate as high as 15% (Anjana et al., 2017). The prevalence of diabetes mellites in the rural areas of India has quadrupled over the last 25 years (Little et al., 2016). Given that India has become an epicenter of global diabetes mellitus pandemic due to the growth rate in the diabetic population, there is a dire need for a novel technology intervention in order to revolutionise the diabetes mellitus management process (Unnikrishnan et al., 2016). Hence, we would like to limit the focus of this conceptual model to the management of T2DM in India.

Why Big Data application?

One of the major recommendations of WHO for the prevention and control of T2DM is to invest in the better management of T2DM, and also recognises that timely intervention, holistic and effective approach to the management of T2DM is the only means to improve the quality of life for the people with T2DM (WHO, 2017, WHO, 2014, WHO, 2013). Patients with chronic conditions such diabetes mellitus generate a large volume of data and these data could be categorized into structured data such as demographic data, semi-structured data such as reports, prescriptions, symptoms, diagnosis, etc. and unstructured data such as audio, video, and other multimedia data. (Raghupathi and Raghupathi, 2014, Westra and Peterson, 2016). Hence, successful management of diabetes mellitus requires the healthcare provider to analyse and process a large volume of structured, semi-structured and unstructured data, which may fall into the category of the big data.

Big Data in the management of Type 2 Diabetes Mellitus (T2DM)

Researchers have agreed that advanced technologies such as big data analytics (Leppert and Greiner, 2016, Raghupathi and Raghupathi, 2014, Stylianou and Talias, 2017) and cloud computing (Sultan, 2014) in combination with wearables (Sagahyroon et al., 2009) and smartphones (Padma and Sharma, 2017) can play a critical role in the holistic management of chronic diseases and can create a new healthcare ecosystem (Bahga and Madisetti, 2013, Qureshi, 2014). Big data analytics and visualisation are increasingly being used in the management of the patient's health to analyse and visualise data with the intention of improving the decision-making process (Krishnan, 2016). Big data analytics is further categorised into prescriptive analytics (AI), predictive analytics (ML) and decision analytics (combination of AI & ML). Raghupathi and Raghupathi (2014) and Stylianou and Talias (2017) recognise that the use of big data analytics in healthcare faces many challenges, and the most important of these being the lack of capability to integrate large volume of data generated by various internal (patient health records & hospital decision systems) and external (government health records, insurance records & patients personal devices) sources.

AI and ML in the management of T2DM

The term Machine Learning (ML) refers to set of automated algorithms with a capability of detecting meaningful patterns in large volume of unstructured data, that could otherwise be not possible to detect (Shalev-Shwartz and Ben-David, 2014). Artificial Intelligence branch of Machine Learning (ML/AI) is a tool that develops a set of algorithms that are able to learn patterns and develop decision rules from the data (Dagliati et al., 2017). Contreras and Vehi (2018) have identified that ML/AI that the use of ML/AI in the field of diabetes research has increased significantly in the recent years and have recognised that ML/AI algorithms can be used for learning from knowledge, Exploration and discovery of knowledge and reasoning from knowledge. For example, Dagliati et al. (2017) developed a systematic approach to use to ML based AI to predict the risk of T2DM patient developing a cardiovascular disease. They developed a simple four step approach comprising of centre profiling, predictive model targeting, predictive model construction and predictive model validation using logistic regression as an algorithm in their predictive model. Buch et al. (2018) recognise that ML/AI is bringing a huge impact on the management strategies adopted in the management of diabetes and suggest that ML/AI can enable enhanced decision making in complex diabetes management situations through interactive applications rather than static documents.

Usability of Big Data Applications in the management of T2DM

Researchers have so far studied the adoption of technologies including big data analytics in various contexts using frameworks such as Technology Adoption Model (TAM) (Zhong and Xiao, 2015, Weerakkody et al., 2017) and Unified Theory of Use and Acceptance of Technology (UTAUT) (Venkatesh et al., 2003). In these studies, perceived usefulness of technology is considered as one of the factors affecting the adoption of technology. Many other researchers who have used TAM or UTAUT models have also indicated that perceived usefulness of technology has a significant influence on the adoption of the technology. But perceived usefulness of technology is not the same as the usability of technology as perceived by the end user of the technology (Mariam and John, 2013).

Perceived usefulness is the perception that creates an attitude towards the adoption of the technology, whereas usability is the ability to use the adopted technology. Although perceived usefulness is studied adequately, no significant attempt has been made to study the factors influencing the usability of big data applications. Since the usability impacts and determines the decision outcomes of the management process, there is a need to understand the factors that influence the usability of a big data analytics application in the management of T2DM. Usability, as perceived by the user of big data analytics applications, is defined as the ease with which the user can learn to operate a big data analytics application, prepare inputs for analyses and interpret the outputs of the application (IEEE, 1990). According to ISO/IEC 9216.2-2005 usability is defined as "a set of attributes that bear on the effort needed for the use and on the individual assessment of such use, by a stated or implied set of users" (ISO, 2005). ISO/IEC 9241.11-1998 standard defines usability as "The extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use." (International Organization for Standardization, 1998).

Literature review indicates that no adequate attempt has been made to study the factors influencing the usability of a specific technology such as big data analytics in a specific context such as management of Type 2 Diabetes Mellitus. While perceived usefulness is a factor that impacts the adoption of a technology, the usability as perceived by the end user is viewed as user experience (UX) metric (Quiñones et al., 2018), a quality metric (Pavapootanont and Prompoon, 2015, Seffah et al., 2001) and a metric that determines the human-computer interaction (HCI) (Carroll, 2002, Dillon, 2001) which determines the desired organisational outcomes from the use of technology. There is adequate evidence in the literature that a well-utilised technology enables improvements in the organisational performance. Hence there is a need to understand what factors determine and impact the usability of technology and it is essential to understand the determinants of usability of a context-specific technology. Moreover, Folmer and Bosch (2004) found that the factors impacting the usability are not being recognised in the architectural stage of system design and there is a need to identify and incorporate these factors while designing an architecture for a new system such as big data analytics rather than just measuring the usability post-implementation.

Product Attributes of AI/ML applications used in the management of T2DM

A structured literature review was undertaken to identify the factors (attributes of big data application) that influence the usability of a software application covering various knowledge areas including standards related to usability, usability measurement models and theoretical frameworks relevant to the usability of a technology component such as a new system, software, or an application. The literature review indicates that usability can be viewed as a top-down approach (model-centric approach) where perceived usefulness is factored in by the software engineers involved in the development of the system or an application. The bottom-up approach (user-centric approach) takes the users' perspectives in the usability of a system or software, and identifies the factors that influence increased use of the system or the software, and thus resulting in improved the organisational decision outcomes (Chin and Jafari, 2013, Jackson, 2012). The review also revealed that most of the studies only focused on usability (perceived usefulness and perceived ease of use) in the top-down approach of adoption using Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). The usability in the bottom-up approach is not adequately researched, especially for rapidly adopted technologies such as big data analytics. in critical industries such as healthcare where human-computer interaction (HCI) is considered critical for the successful delivery of the service. The significance of usability is evident in the literature review from the extent of literature available on the measurement of the usability post-implementation of a system or software, including in the healthcare industry.

Big Data Characteristics

Big data refers to a new paradigm of data that has certain unique characteristics due to which it cannot be processed and analysed using normal data analysis applications (Ahmed and Ameen, 2017). Big data is different from the normal data in terms of its characteristics and these characteristics significantly impact the systems or applications that are designed to use big data (Reddi and Indira, 2013). Since the usability of the system is significantly impacted by its design aspects, there is a need to understand the characteristics of big data, so that 'their impacts on the system design and thereby the usability of the system can be analysed (Folmer and Bosch, 2004).

The four main characteristics of big data that differentiates it from the normal data are the Volume, Velocity, Variety, and Veracity (Lee, 2017). Volume refers to the quantity or the size of data measured in bytes. While the size of normal data is measured in gigabytes, the data must be at least 1 terabyte to qualify as big data. The size of big data usually runs into petabytes (1024 terabytes) or exabytes (1024 petabytes) (Oguntimilehin and Ademola, 2014). Velocity refers to the rate at which the data is generated and processed to provide insights to the users. Normal data is generated and processed at a very slow rate, whereas big data is generated and processed at a very fast rate (Kaisler et al., 2013). Variety refers to the different types of data. Data can be classified broadly into structured, semi-structured and unstructured. Data can also be classified as text, photos, audio, video, etc. Normal data is structured in nature and generally made up of text. Big data can have any of the above structures and forms (Kaisler et al., 2013, Lee, 2017). Veracity refers to the quality, reliability, and certainty of the data sources, usually caused by incomplete, inaccurate, latent, subjective, and deceptive data. Normal data has least veracity, whereas big data may possess a high level of veracity due the above three characteristics (volume, velocity & variety) and requires special attention to reduce or overcome these quality-related issues (Kaisler et al., 2013, Lee, 2017).

Big data characteristics and attributes of AI/ML application

Investigation into current literature on design and development of big data analytics applications such as ML/AI reveal that very little research is being undertaken on the impact of the big data characteristics on the big data analytics application development process. Current research predominantly focuses on the obvious aspects of big data application such as collection, organising and storing the data and unfortunately very little is being done to highlight the significance of big data attributes in the software engineering process and usability of such applications (Al-Jaroodi and Mohamed, 2016).

The main challenge to a big data analytics application is the ability to handle the large volume of data being generated at very high velocity from a variety of sources, while ensuring the reliability, integrity and security of the data while the application is being used by the end users. Al-Jaroodi and Mohamed (2016) recognised that characteristics of big data would impact the big data application attributes such memory management, communication and networking, integrity, reliability, security, privacy, accuracy and outputs. The characteristics of big data also impacts big data application attributes such as scalability of application, software architecture, software deployment, ability to handle data replication and inconsistencies, execution logs, fault tolerance in addition to above mentioned attributes (Karakaya, 2017).

Conceptualizing the research model

From the literature review, it was observed that there is limited literature available that identify the characteristics of big data generated in a health care context, and none of them clearly identify the characteristics of big data generated in the management of T2DM. There is also limited research on the impacts of big data characteristics on the big data applications and none of this literature is specific to big data applications used in the management of T2DM. There is a considerable amount of literature referring to the usability of various applications in generic healthcare contexts, but a large gap exists in the literature on usability studies related to big data applications used in the management of T2DM. The void is so clear that there is a lack of literature on the taxonomy of the clustered factors and moderating variables.

Current literature predominantly focuses on the adoption of big data applications in a generalised healthcare environment or some specific contexts other than T2DM. Although researchers agree that adoption will lead to successful outcomes only when the new system is utilised effectively by the users, there is lack of research on the factors contributing to utilisation (usability) of a new system, more specifically, a big data application. Hence, this research would focus on the impact of the healthcare big data characteristics on the usability factors and tries to identify those factors that would influence the usability of big data applications in the management of T2DM. There is also a gap in terms of availability of usability measurement models for the big data applications in the healthcare context.

Based on the literature review undertaken so far, it could be established that: Inadequate literature is available on the relationship of characteristics of big data and the product attributes of the big data application; Inadequate literature is available on the relationship between big data product attributes and the usability of the big data application for the management of T2DM in India; Inadequate literature is available related to contextual factors that could have an influence on the usability of big data applications for the management of T2DM in India.

The below model is proposed with the aims to (1) identify the attributes of big data application that may impact the usability of the application and to identify characteristics of big data that would impact the product (big data application) attributes; (2) identify the big data application attributes that are relevant in the management of T2DM and studying their impact on the usability of a big data analytics application in the management of T2DM; (3) understanding and defining a holistic management process of T2DM by identifying all the context related factors such as users, tasks, and environment associated with the management of T2DM. These factors would form the moderating variables that would influence the impact the attributes of big data application would have on the usability; (4) to identify all the sources of data and types of data that is required in developing a holistic big data application architecture within the context of T2DM management; (5) combining the findings from above to develop big data analytics usability measurement model that can be generalised for use in similar contextual situations.

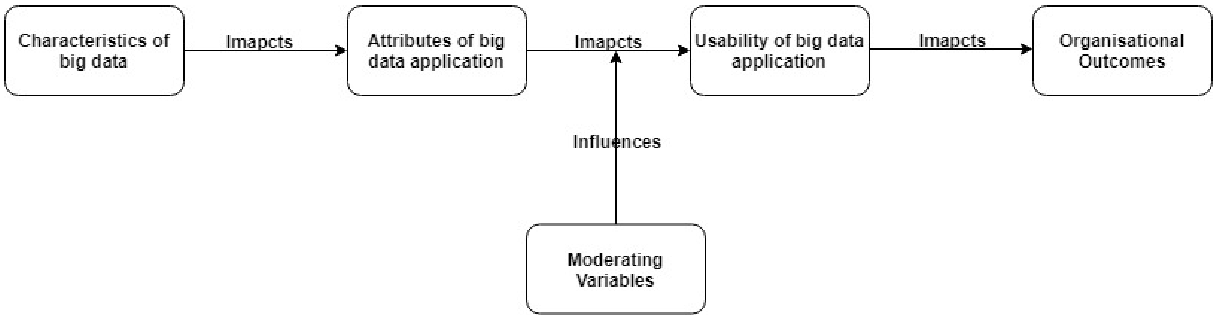

Figure 1: Conceptual Research Model

RESEARCH DESIGN AND METHODOLOGY

The conceptual model could be tested using both qualitative and quantitative methodologies. In the first stage of the research, qualitative research using a semi-structured interview could be used to establish the taxonomy of the clustered factors, identify the components of each cluster and establish the relationship between each cluster. In the second stage of the research, the established research could be tested using a quantitative methodology with the help of a survey. This will enable not only help identify the big data usability model but also let us generalise this model to various contextual situations.

EXPECTED OUTCOMES

This research would contribute to the academic literature in the areas of Information Systems Quality, Human-Computer Interaction (HCI), design and development big data applications, usability engineering, user experience (UX), and usability measurement model. As discussed in the previous sections, usability is a significant factor determining the quality of information systems and this research on the usability of big data application would enable identify the factors affecting the usability of the information system, and thereby the quality of information system. This research would also contribute significantly to the area of human-computer interaction as some of the factors affecting the usability are related to this specialisation. Since the broad aim of this research is also to study the impacts of the characteristics of big data analytics on the usability factors, this research would also contribute to the design and development of big data applications. Both the impacts of characteristics of big data on factors affecting the usability and impact of these factors on usability are to be considered by the software engineers while designing and developing user-friendly systems. Hence it is believed that this research would also make significant contributions to usability engineering as well as user experience. The aim and contribution of this research to the academia will be the development of a big data application usability measurement model which would enable future researchers to apply it various healthcare and non-healthcare contexts.

Expected contribution to the industry

The contributions from this research would benefit the healthcare industry, predominantly that part of an industry that is directly involved in the management of T2DM and indirectly involved in the management of comorbidities on T2DM. Although this research is focused on T2DM, the contributions of this research can be far beyond T2DM and the learning from this research can be applied to the management of any chronic condition. In addition to the healthcare industry, this research would also help the Information and Communication Technology (ICT) industry, specifically the section of industry that is involved in the management of Information Technology. In addition to this, another section of the ICT industry, that would immensely benefit from this study is the developers of Information Systems as this research would provide a lot of insights into the usability, human-computer interaction, and software quality aspects of designing the Information Systems.

LIMITATIONS

One of the major limitations of this research model is the context under which the model is being developed. The context is limited to management of T2DM in India. Since the population of India is culturally, ethnically and genetically different from the other countries where the prevalence of T2DM is high, the model may require modifications to suit a different context. The second aspect of the context is the limitation of studying T2DM as a chronic condition. The conceptual model must be appropriately adjusted to understand the usability of big data applications in the context of a different chronic condition. The last major limitation of the research model is its limitation to big data applications. To study the usability of any other information system application, the model must refine to suit the attributes of that specific application.

CONCLUSIONS

It can be concluded from the investigation that T2DM is on the rise and emerging to be a major health concern for the developing nations, especially in India. A review of the literature indicates that big data applications can play a major role in the management of T2DM and the adoption of such applications are on the rise. But the desired outcomes of the adoption of the big data application can be envisaged only when the big data applications are utilized. It is clear from the literature review that there hasn't been adequate research on the usability of the big data applications in the management of T2DM and currently there is no usability measurement model available for big data applications. This research aims to address these gaps by attempting to identify the factors impacting the usability of big data application in the management of T2DM in India. The research also attempts to develop a big data analytics usability measurement model that can be used in similar contextual situations. The outcomes of this research would contribute to the academic literature in the many areas of Information Systems.

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