Using Machine Learning to address Data Accuracy and Information Integrity in Digital Health Delivery

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Abstract

Today, much of healthcare delivery is digital. In particular, there exists a plethora of mHealth solutions being developed. This in turn necessitates the need for accurate data and information integrity if superior mHealth is to ensue. Lack of data accuracy and information integrity can cause serious harm to patients and limit the benefits of mHealth technology. The described exploratory case study serves to investigate data accuracy and information integrity in mHealth, with the aim of incorporating Machine Learning to detect sources of inaccurate data and deliver quality information.

Keywords: Data Accuracy, Information Integrity, mHealth, Machine Learning, Diabetes

1 Introduction

Reports from the World Health Organization (WHO) indicate that noncommunicable diseases are the leading cause of deaths worldwide, where the number of deaths from

2012 are projected to increase from 38 million to 52 million by 2030 (World Health Organization, 2014). Noncommunicable diseases according to WHO, are chronic diseases such as cardiovascular diseases, cancers, respiratory diseases and diabetes. Chronic diseases along with change in demographics, increasing costs of medical services, ongoing quality and safety issues in healthcare, are all major challenges to the delivery of healthcare services (Armstrong et al., 2007). These healthcare challenges mean finding new, effective and innovative solutions that ultimately lead to decreasing the pressure on Healthcare systems. Given today's digital economy, it appears logical to look for technology enabled solutions such as mobile phones.

The number of mobile phone subscriptions as per the 2015 statistics released by the International Telecommunication Union, is 7 billion worldwide (International Telecommunication Union, 2015). This presents an opportunity for mobile phones to be used as an intervention in the rising number of chronic diseases and for health management. As half of smartphone owners frequently browse for health information online and monitor their health using mobile health applications (Fox & Duggan, 2012), this gives mobile phones a new capacity to be used as mobile health. The definition of mobile health (mHealth) is the use of portable devices such as smartphones and tablets to improve health (Hamel et al., 2014).

While smartphones have a new role to play in the effective management of health and diseases, the technology must be clear of any medical errors. A medical error has been defined as a preventable adverse outcome that results from improper medical management (a mistake of commission) rather from the progression of an illness due to lack of care (a mistake of omission) (Van Den Bos et al., 2011). Errors in the medical field belong to a number of domains such as development and use of technologies, ergonomics, administration, management, politics and economics (Vincent, 2010).

A common root cause of medical errors is human error, where errors are of omission (forgetting to do something) and commission (intentionally doing something that is not meant to be done) (Health Informatics: improving patient care, 2012). However, medical errors have progressed from human to technological errors. Jenicek (2010) defines technological error in medicine as errors that relate to data and information recording, processing, and retrieval caused by information technology and its uses (information technology inadequacy and failure).

Using mobile phone technology as mHealth devices, has its own set of challenges. These challenges relate to data (accuracy, integrity, privacy, security and confidentiality) and information integrity. To break through these challenges and benefit from such promising technology, techniques such as Machine Learning, which apply probabilistic reasoning after the analysis of data, can help deliver robust and accurate mHealth solutions.

2 Literature Review

This section explores key areas of mHealth by first examining sources of inaccurate data, then information integrity and the role of Machine Learning in Healthcare.

2.1 Data Accuracy

At the centre of mHealth solution is data. The term data itself can be defined as information in the form of facts or figures obtained from experiments or surveys, and used as basis for making calculations or drawing conclusion, as defined by Dumas (2012). Accuracy according to WHO, is the original source of data and it is an element of data quality that is intended to achieve desirable objectives using legitimate means (World Health Organization, 2003). The quality of the data helps in evaluating health, assess effectiveness of interventions, monitor trends, inform health policy and set priorities (Van Velthoven et al., 2013). When data lacks accuracy, currency or certainty, it can have catastrophic results (Sadiq, 2013).

For mHealth solutions to be effective, the data collected from mHealth devices, wearables, and applications must be accurate and secure (Mottl, 2014). Accurate data ensures proper assessment and treatment of patients. Some of the traditional methods of assessing patients provide inaccurate data (Lin, 2013). The common standard for data collection in the medical field is direct observation. Direct observation is the observation of patients and the different patient characteristics at the clinic (Flocke & Stange, 2004). This allows for the collection of accurate data by directly observing the patients and their symptoms (Eisele et al., 2013). This standard is missing in mHealth solutions as there's no direct observation of patients by the medical professionals during data collection.

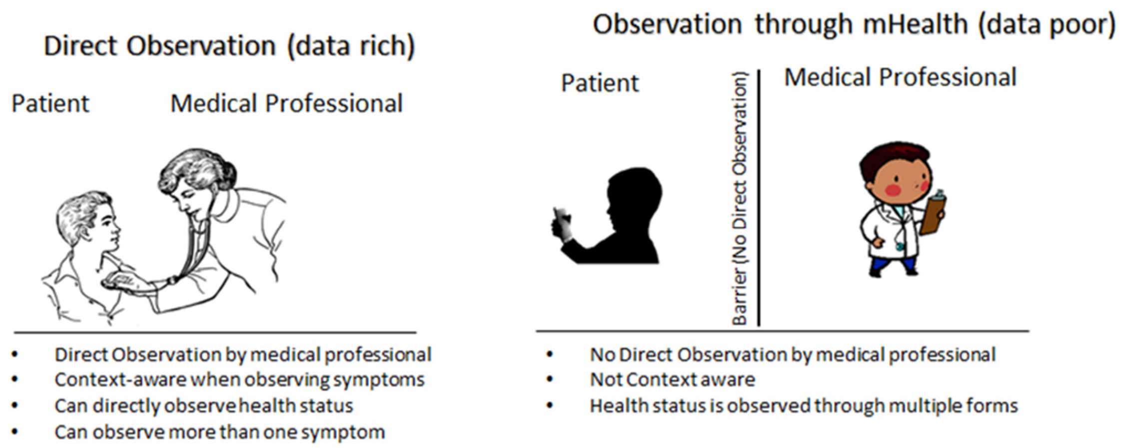

Figure 1: Direct Observation compared to Observation through mHealth (Characters obtained using Microsoft Online Pictures)

Figure 1 is an illustration of how observation through mHealth differs from the traditional direct observational method. This can introduce the risk of not conveying the full picture of a patient's health status.

The common methods of data collection in mHealth is through data entry by users or collected automatically if it is a sensor based solution. The issue of data inaccuracy can be classified into four categories. These categories are initial data entry, data decay, moving and restructuring, and using data (Olson, 2003).

1. **Initial Data Entry:** Mistakes, Data Entry Process, Deliberate, System Errors.
2. **Data Decay:** Accuracy of data when originally created over time
3. **Moving and Restructuring:** Extracting, Cleansing, Transformation, Loading, Integration
4. **Using:** Faulty Reporting, Lack of Understanding

In addition to the four (4) categories described above, intentional and unintentional wrong data entry and the speed at which data is collected can be misleading. Misleading data results in misallocating resources or interventions when needed for the patients (Patnaik, Brunskill, & Thies, 2009). Inaccurate readings, insufficient amount of data, movement and physical activities also contribute to inaccurate data provided through the mHealth devices (Mena et al., 2013). Another factor that affects the quality of the data is security breaches, where unauthorized modification or alteration is made to patients' data that compromise their confidentiality and privacy (Mena et al., 2013).

Concerns associated with data accuracy and validity are persistent and can become a risk to patients' safety (Linda, 2012). mHealth solutions must deliver accurate data. For data to be accurate, it must always consist of completeness, consistency, currency, relevance and accuracy (Narman el al., 2011). In mHealth, these elements of data quality can be compromised as data goes through 5 different stages. These are: (1) Collection, (2) Transmission, (3) Analysis, (4) Storage and (5) Presentation (Klonoff, 2013). This means data must be accurate and consistent over its entire life-cycle in order to conform to data integrity (Cucoranu et al., 2013).

Inaccurate data does not only affect data integrity, but also the information that are generated based on the collected data. This can compromise the integrity of the information and thus mislead patients and misguide treatments.

2.2 Information Integrity

Information at the very basic level, is raw data that is processed and transformed into information, from which then knowledge is extracted (Dumas, 2012). In mHealth, Information must conform to integrity. The Integrity of Information is about having the right properties of information including sensitivity in which information is used, as well as encompassing accuracy, consistency and reliability of the information content, process and system (Fadlalla & Wickramasinghe, 2004). mHealth can be used in a number of ways for the treatment of patients and delivery of healthcare services. It is vital that the information generated is accurate in order to avoid misdiagnosis, delayed care seeking, incorrect self-treatment, conflict over appropriate care or non-adherence to treatment and medication (Kahn, Yang, & Kahn, 2010).

The shift from clinician care towards patient centred model is encouraging patients to actively self-manage and make decisions concerning their health (Boulos et al., 2011). To sustain self-management using mHealth, patients must be provided with accurate information that are of high integrity. The integrity of information produced as a result of shift in the dynamics of technology has been getting more focus as the interaction experience has changed (Cunningham, 2012). What causes information to lack integrity is errors in healthcare systems due to data loss, incorrect data entry, displayed or transmitted data (Bowman, 2013).

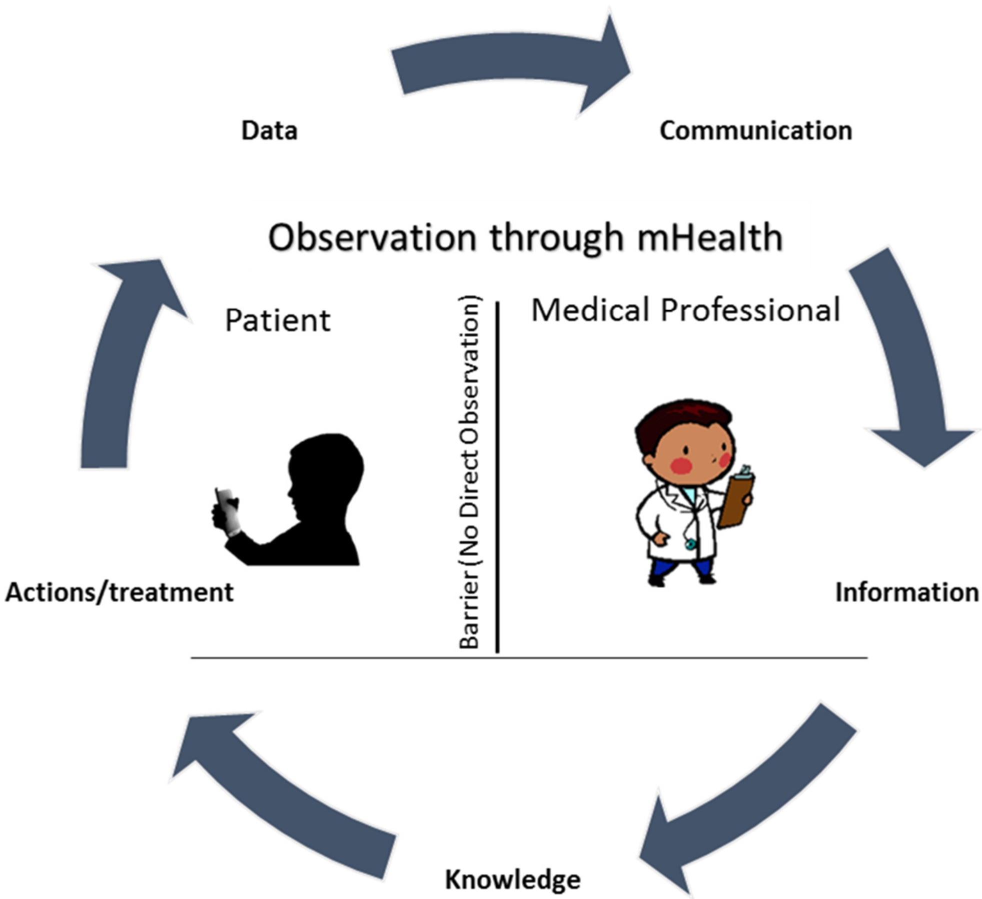

Figure 2: Transformation of data into knowledge in order to provide treatment (Characters obtained using Microsoft Online Pictures)

During the data collection stage, if the data is inaccurate, it continues through the data transformation cycle (See Figure 2). When data reaches the medical Professional, they apply their reasoning based on the provided data, from which then a recommended set of actions or treatment is suggested. If Information that's circled during this process lacks integrity, the outcome of the treatment or suggested set of actions can unintentionally harm the patient.

To treat patients correctly using mHealth and ensure information integrity, then data governance, information workflow management, internal controls, confidentiality and data privacy processes must exist (Flowerday & Solms, 2010). These processes along with information technology can improve the quality of care by decreasing medical errors due to inaccurate and untimely information (Mahmood et al., 2012). Using a semantic tool when processing data and transforming it into information, can prove critical in detecting errors in data and ensuring information are of relevance to the patients and treatments. One common and publicly available semantic tool is the Omaha System. The Omaha System 'is a complex, multi-axial, hierarchical, relational standardized health services taxonomy' as explained by (Monsen et al., 2009). The Omaha System has been integrated into software programs, recognized by nursing associations, and is in agreement with the International Organization for Standardization (ISO) (Monsen et al., 2009). The three (3) components of the Omaha System (See Figure 3) are the Problem Classification Scheme, the Intervention Scheme, and the Problem Rating Scale for outcomes. The first component of the Omaha System enables healthcare professionals to collect assessment data such as signs and symptoms, intervention scheme to design intervention and it is driven by the provider, and lastly is an outcome measurement scale for evaluating the interventions and the care process (Topaz, Golfenshtein, & Bowles, 2014).

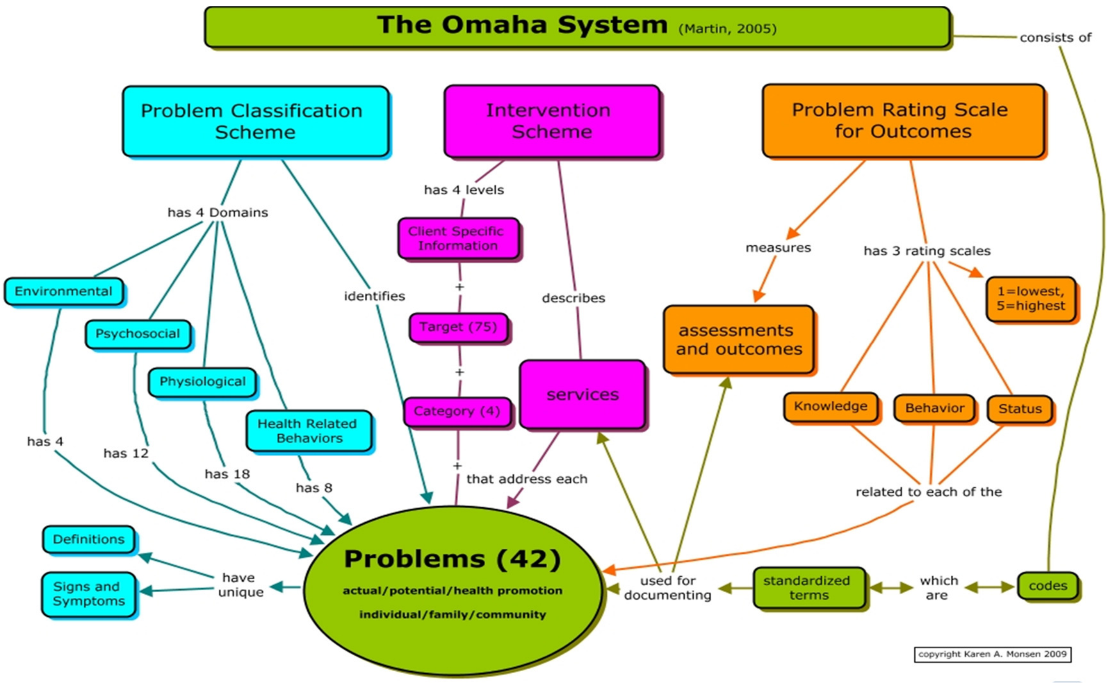

Figure 3: The Omaha System 2005 version (Adapted from The Omaha System Chart, 2015)

Using the Omaha System in an accurate and consistent way, would establish an effective basis for documentation, communication, coordination of care and outcome measurement (Garvin et al., 2008). Incorporating Omaha System in mHealth, can potentially increase the accuracy of data and information.

Elements from the Omaha System have also been incorporated into Machine Learning Algorithm studies (Monsen et al., 2009). This offers a role for Machine Learning to be adapted in mHealth technology to improve the detection of inaccurate data using the standardized taxonomy, that would enhance the quality and delivery of information of high quality.

2.3 Role of Machine Learning in Healthcare

Machine Learning has enabled smarter use of data in health by shifting from curing diseases to anticipating and preventing them before they occur through real time data analysis (Kumar et al., 2013). The prediction of diseases is the result of analysing large amount of data through different mHealth tools (Figure 4).

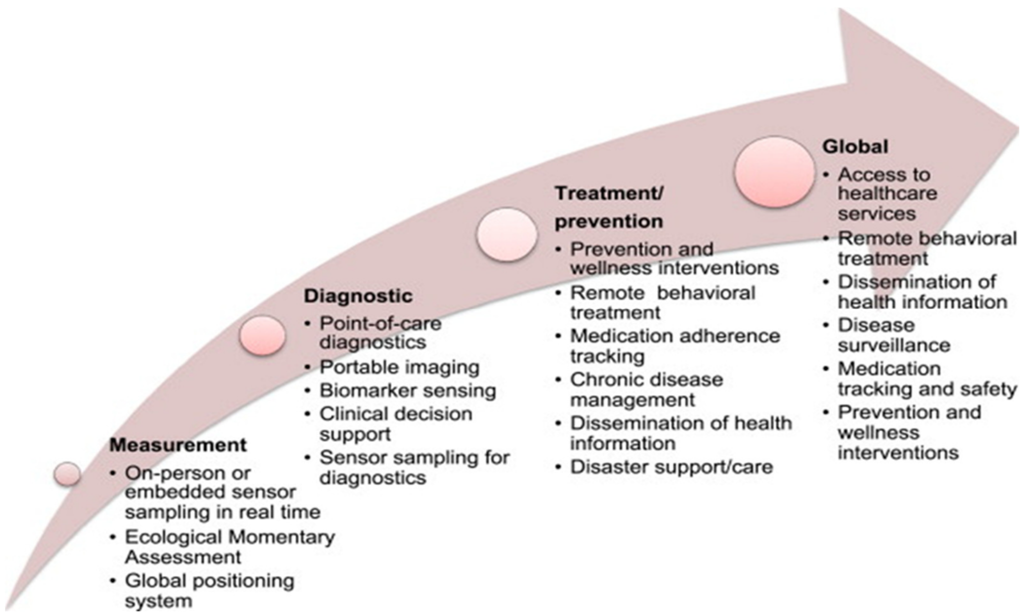

Figure 4: Continuum of mHealth Tools (Adapted from Kumar et al., 2013)

mHealth can be used as a tool for different purposes, such as the measurements of GPS locations and sensor readings, diagnosis, treatment and prevention, and access to global healthcare services. Despite the opportunities and benefits mHealth brings, the risk of medical errors occurring in mHealth must be constrained. Varshney (2009) describes common medical errors as those found during investigation, diagnosis, treatment, communication and office administrations errors.

Constraining these errors during those stages can be achieved by learning about the collected data and applying analysis techniques to find sources of inaccurate data. The analysis performed by Machine Learning, extracts new knowledge when there is great amount of data (Lambin el al., 2013). The machine learning algorithms learn and improve the outcomes through experience and observation (Oquendo et al., 2012).

The concept of Machine Learning is – Learning that improves with experience at some task. That is (Bell, 2014):

- Improve over task, T
- With respect to performance measure, P
- Based on experience, E

Machine Learning algorithms can play a pivotal role in acquiring accurate data through pre-trained algorithms that can be deployed in mHealth solutions. Support Vector Machines (SVM) algorithm was deployed in a blood pressure measurement application on an android tablet that detected the patient's arm and ensured stability, in order to acquire accurate reading of the data performed by the cuffs (Murthy & Kotz, 2014). In a fall detection scenario, recorded data were used from a database which contained 95 instances of recorded falls, from which then four types of machine learning algorithms were applied to accurately detect a fall (Sannino, De Falco, & De Pietro, 2014).

The role of Machine Learning in detecting inaccurate data through reasoning, could prove crucial in enhancing the quality of the data collection stage of mHealth, as the accuracy aspect of data is a major challenge in itself. Removing inaccuracy and assuring high data quality, would result in a deluge of solutions that can be developed to help manage diseases to reduce healthcare costs.

With Machine Learning having a role in the delivery of mHealth, the proposed study is to investigate data accuracy and information integrity in the context of mHealth solution by addressing the research question:

How can Machine Learning be applied in mHealth solutions to provide data accuracy and Information Integrity?

3 Conceptual Model

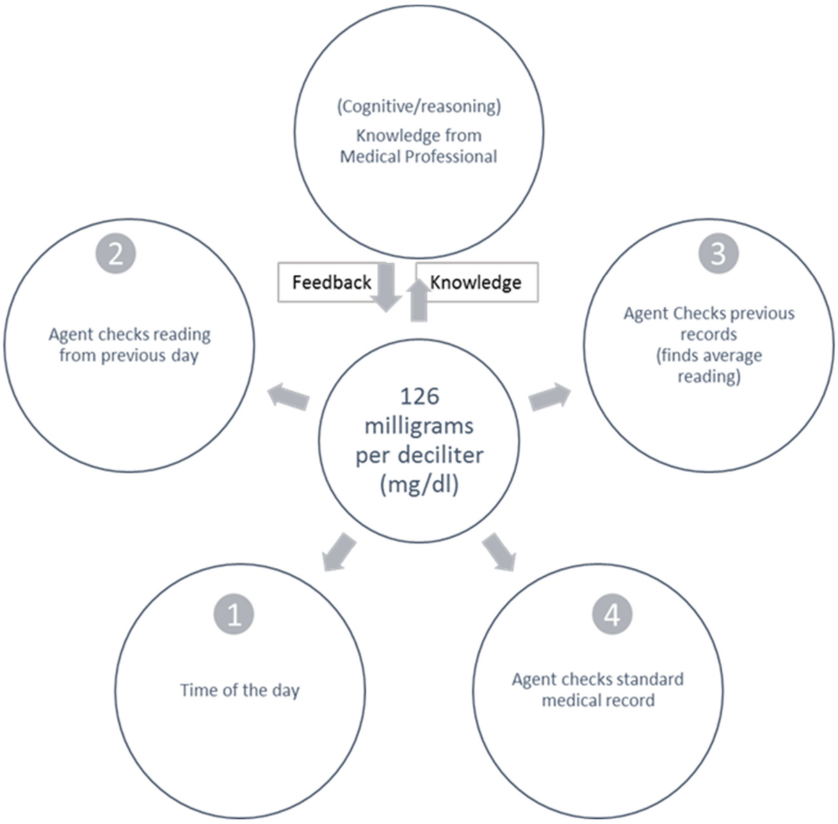

Figure 5: Conceptual Model

To help address the accuracy problem in mHealth, the conceptual model (See Figure 5) has been developed to facilitate the detection of data inaccuracy in mHealth and draws on providing high quality information using multiple agents. The conceptual model is built using the elements of data integrity that prove critical to generating high quality information that is free of errors.

The four (4) agents described in the conceptual model can perform smart functions which help detect and assess the accuracy of the value that is received from a patient during the use of mHealth:

1. **Time of the day:** The function of this agent is to check for data decay, currency and timeliness, which makes the treatment and actions to be relevant and provide information in a timely manner. Thus ensuring no delay in seeking treatment and allows for monitoring of the patient to be more relevant.
2. **Reading from previous day:** The function of this agent can detect mistakes by comparing the current value against what was provided previously. Where there’s a significant difference, it will notify the medical professional of such event to raise awareness about the change in the value.

3. **Average value from previous reading:** The advice given to a patient during mHealth treatment is often based on the current value and does not take into an account the history of the patient. This agent performs calculations that finds the average value as well as providing a better insight of the patient's behavior by providing a trend using the available historical data.
4. **Medical standards:** This agent checks the current value against the standard, acceptable medical reading that is of the right range and conforms to medical data definition related to the disease.

4 The Proposed Research Methodology

In addressing this study's research question, a qualitative research method is applied using an exploratory case study. The following justifies the chosen research method, data collection, analysis and reporting.

4.1 Single Case Study

Yin (2014) defines case study as 'an empirical inquiry that investigates a contemporary phenomenon (the "case") in depth and within its real-world context, especially when the boundaries between the phenomenon and context may not be clearly evident'. Case studies are not considered a methodology but rather a choice of what is to be studied (Denzin and Lincoln, 2011), and they are for studying a single group, event or person (Donley, 2012). The selected case study is a mHealth solution for diabetes, with the case being patients' data. The selection of the case is guided by two principles. First is the form of question posed in this research where the form is 'How', requires no control over behavioural events (no control over how the data is produced) and focuses on contemporary events as the case (patients' data) is studied in its real-world context.

The second principle in selecting such case study is the single-case study rationale where the case is critical to the theory (Yin, 2014) and relevant to the research question. Treating patients via mHealth rather than at the clinic could allow a gap for errors. Accessing such case study, enables the research question to be addressed by examining patients' data and exploring the characteristics of the data, the intended meaning when data was produced and how it contributes towards the treatment of the patient.

4.2 Data Collection

The type of data collected for this study is qualitative secondary, de-identified data of patients with diabetes. Secondary, de-identified data is data that is used for research purposes and do not identify or represent a person (McGraw, 2012). The de-identified data will be of records of patients who have diabetes and contain information such as time and date of measurement, glucose reading and a description of the reading. The chosen method of data collection seeks data that presents a chronic disease that is relevant to the case study, it is produced by people in real world and is authentic.

4.3 Data Sampling

With the proposed method of data collection being Secondary data, the sampling technique employed in this study is convenience sampling. The selection of this sampling technique is due to the readily available and accessible secondary data that is used for this study, and conveniently recruited (Gideon, 2012) through two sources. The first sample is diabetes data from clinical solution for the treatment of diabetes, while the second source is data from mHealth solution. The sample represents one of the many developed mHealth solutions and the data characterize the type of data created when using mHealth.

4.4 Data Triangulation

The data is triangulated using triangulation of different data sources of information by separating the secondary data into different data sets to build coherent justification for themes (Creswell, 2009). The datasets will be numbered to represent different patients and for triangulation to confirm the accuracy of the findings.

4.5 Data Analysis

The data analysis is performed using Thematic and hermeneutics techniques. Thematic analysis is will be applied to aid in the interpretation of the texts by coding the data into organized segments of texts before bringing meaning to information (Creswell, 2009), and later underlining them for generating themes that describe passages in the data (Cohen, Steeves, & Kahn, 2000). In analysing the themes, Hermeneutics analysis is used to provide a detailed description of the text to capture and communicate the meaning of the lived experience (patients using mHealth) being studied (Cohen, Steeves, & Kahn, 2000). This is to seek interpretation of the mHealth data and understand the meaning of it, accuracy of the values and what the producers of the text initially intended it for (Flick, Kardorff, & Steinke, 2004).

5 Limitations

A key challenge for this research that requires mentioning is the use of secondary data. Using secondary data does not allow this research to observe the patients nor their behaviour during the use of the mHealth solution, specifically when the patient enters the data. Thus, this research does not take into consideration the human factors that can affect the accuracy of the data. Despite this difficulty, this is a major challenge in mHealth as there’s no direct observation of the patient or their behaviour when the data is collected. Using the secondary data helps establish methods that can overcome this challenge and ensure data accuracy and information integrity in mHealth through the use of machine learning.

Another limitation is the study's focus on a single chronic disease, diabetes. Diabetes is one of the many chronic diseases listed by World Health Organization. However, treatment of diabetes through mHealth is achieved through the transmission of text data that contain diabetes related information, which allows for the testing of Machine Learning algorithms to be done.

6 Discussion and Conclusion

The preceding serves to present a research in progress study that focuses on trying to optimize data assets for mHealth contexts. In particular, it focuses on critical considerations regarding data accuracy and information integrity. While still at an early stage, the research should provide important implications for theory and practice.

From the perspective of theory, the study will assist in developing a new area of knowledge that establishes methods similar to direct observation in mHealth using Machine Learning as a step to validate the accuracy of the data. As mHealth grows and the domain of consumer health informatics matures, we will see more and more mobile solutions being embraced to support health and wellness. Central to the success of these solutions is that they provide accurate data and information to consumers who in turn make decisions with far reaching implications and consequences based on the data and information received. The findings from this study will clearly be significant in ensuring optimal value from such mHealth solution. Upon the completion of the study, it will contribute to the hermeneutics field in information systems, and a reference for researchers to use analyse future empirical mHealth related studies and assist in the interpretation of their analysis.

Finally, given today's digital economy, findings from this study are relevant to not just for healthcare but transferable to other industries also concerned about accuracy of data input and information integrity.

7 Future Research Directions

The future direction for this research is to access the secondary data and complete the analysis (Figure 6). The findings from the analysis will then be used to identify the gaps with the current mHealth solution and match them with the most appropriate Machine Learning Algorithm. The selection of the algorithm will be based on one that best matches the conceptual model.

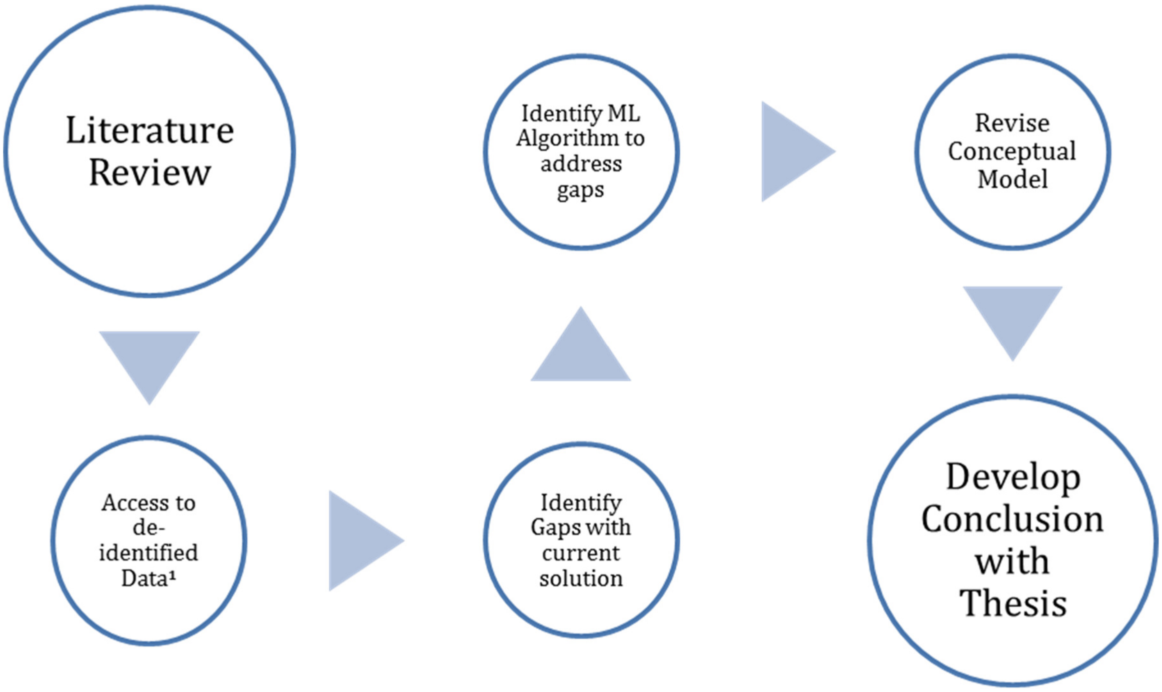

Figure 6: Flow of future research direction

Thus, a key expected finding from this study is an appropriate framework for streamlining the process of data collection in mHealth to include Machine Learning to assist in classifying data as they are captured to reduce erroneous data. Such a framework will have significant value to practice in a digital health environment.

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