Simulation and Implementation of Mobile Technology Resources to Enhance Healthcare Service Delivery for Breast Cancer Patients in Developing Nations

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Abstract

Breast cancer is one of the deadliest diseases among women. This is especially true in developing nations such as South Africa. As a response to the breast cancer epidemic, AstraZeneca established the Phakamisa health initiative. In this paper, research is proposed that could potentially aid AstraZeneca's Phakamisa program. The proposed research will be implemented in two phases. The first phase involves the development and implementation of a mobile health platform. The second phase consists of the creation of a simulation model which will be used to analyze and optimize the effectiveness of the Phakamisa program.

Keywords

simulation modeling, healthcare, and mhealth

1. Introduction

Breast cancer is the deadliest cancer among women around the world. According to research conducted by GLOBOCAN in 2008, 1.38 million people were diagnosed with breast cancer in a single year (Ferlay et al., 2010). The GLOBOCAN series of the International Agency for Research on Cancer has reported around 1.7 million diagnoses of breast cancer in 2012 (Ferlay et al., 2015). The survival rates vary with the health and treatment facilities available in the country, but it has been observed that African countries have the lowest rate of survival after five years of cancer diagnosis (World Cancer Research Fund International, 2012). In South Africa, the most prevalent type of cancer diagnosed among females is breast cancer and has been responsible for 16% of deaths. The diagnosis is usually identified at a later stage, like other developing countries, resulting in higher mortality rates due to lack of proper screening facilities. This consequently leads to an increase in risk over time with some women ignoring it with the notion that it might go away with time (Moodley, Cairncross, Naiker, & Momberg, 2016).

Doctors in South Africa have cited multiple reasons behind the high mortality risk of breast cancer among women. The major factors have been identified as inadequate screening programs and facilities that impede doctors abilities to diagnose symptoms properly. Doctors report that most of the patients abandon hope due to either financial constraints or no support from the society (Moodley, Pathways to breast cancer care in South Africa, 2017). There is limited knowledge (published in print and digital media) readily available about breast cancer in South Africa. It is this limited knowledge which disproportionately affects those living in rural areas. Patients who were diagnosed with late-stage cancer reported that they had no information about symptoms that they should have been informed at an earlier stage especially the patients live in the rural areas (Moodley, Pathways to breast cancer care in South Africa, 2017).

As a response to the breast cancer epidemic in South Africa, AstraZeneca, a multinational biopharmaceutical company, established the Phakamisa health initiative. According to AstraZeneca's website, the Phakamisa initiative is an access program for patients with Breast and Prostate cancer which aims to help raise breast cancer awareness, increase early detection and diagnosis, and improve access to treatment and effective support networks. The core of the Phakamisa initiative is the education of health professionals and volunteers from community referred to as navigators. According to AstraZeneca since 2011, 600 health professionals and 400 navigators have been trained and educated to help support breast cancer patients. To date, approximately 1.3 million South African women have been impacted by AstraZeneca's Phakamisa program. The research proposed in this paper aims to assist AstraZeneca in its goal of impacting 3.5 million South African women by the year 2021. The proposed research will be implemented in two phases. The first phase involves the development of a mobile health platform. The second phase of the research consists of generating a simulation model of Phakamisa which would be used as an analytical and optimization tool to enhance the effectiveness of the program.

2. Phase 1

2.1 Mobile Health Care Platform

There are many obstacles facing healthcare systems in developing countries that prevent the healthcare system from providing a high-quality service. One of those obstacles is the financial source limitation and the second is a lack of qualified healthcare providers. Especially in rural areas, these challenges are magnified due to the difficulties of the patient being able to travel to the healthcare facility. As a potential solution to these problems, developing countries have put forth a more concerted effort to provide high-quality service. The adoption of a mobile health (M-health) platform was one of these proposed solutions due to the benefit of a minimum financial cost, while still introducing high-quality service. M-health is defined as the practices of healthcare workers supported by a mobile device such as cell phone, personal digital assistants, and patient monitoring devices.

The M-health platform has been adopted in several areas of healthcare. These areas include disease prevention (Cole-Lewis & Kershaw, 2010), data collection and storage in hardware which can be accessed by different medical centers (Tomlinson et al., 2009), and diagnosis of diseases. The M-health platform aids in the diagnosis of diseases by communicating and connecting with patients (Breslauer et al., 2009). Figure 1 shows the different applications of M-health technology in healthcare.

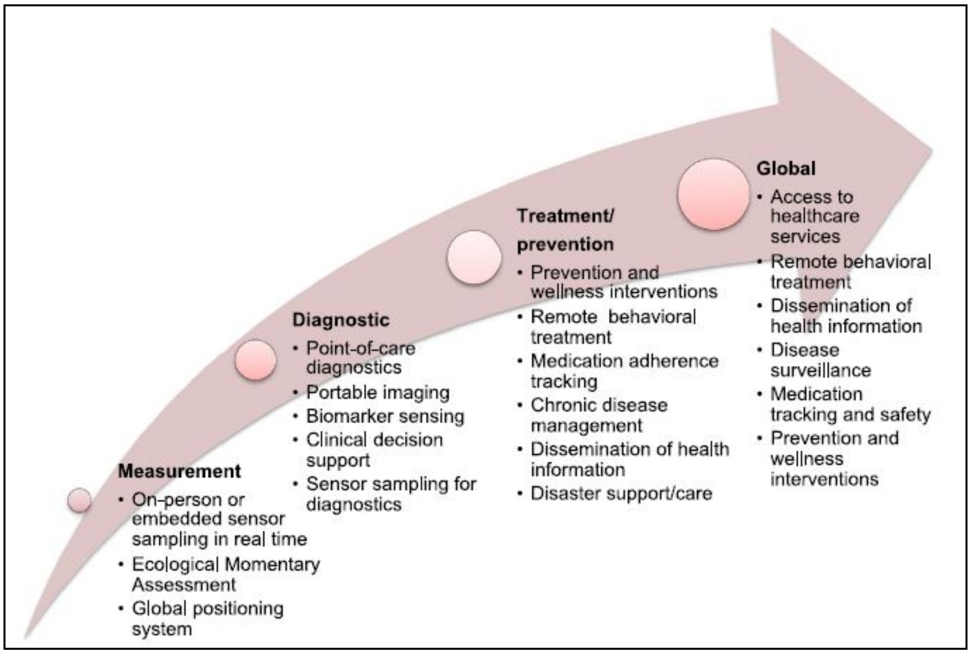

Figure 1. Applications of M-health technology (Kumar et al., 2013)

2.2 Implementation of the Mobile Healthcare Platform Mobile Healthcare Platform

Phase 1 of the proposed research is to integrate a mobile health platform that can communicate, connect, store the data and make it available anytime that medical staff needs it for diagnostic purposes. It is a system that provides several services that patients with breast cancer in rural areas that may need. Also, this platform will support local healthcare providers in communicating with the patients on a regular basis. The mobile health platform will consist of two major units which are the patient/healthcare provider component, and the intelligent management component as shown in figure 2. The patient/healthcare provider component consists of two units which are the patient's units and the healthcare provider units. The patient's units will consist of a cell phone that has the M-health platform, and any additional mobile devices that can help the medical staff diagnose the patients remotely. The healthcare provider units consist of a web interface and any mobile device that has the M-health platform. This will allow the healthcare providers to the track a patient's daily vitals, which in turn allows the patient to monitor their condition better. An intelligent management component will consist of a data-based model, an intelligent decision support model, an educational model, and local healthcare providers support model. This mobile health platform will help reinforce AstraZeneca's Phakamisa goals of training, development, education, and awareness by the services embedded in the mobile health platform.

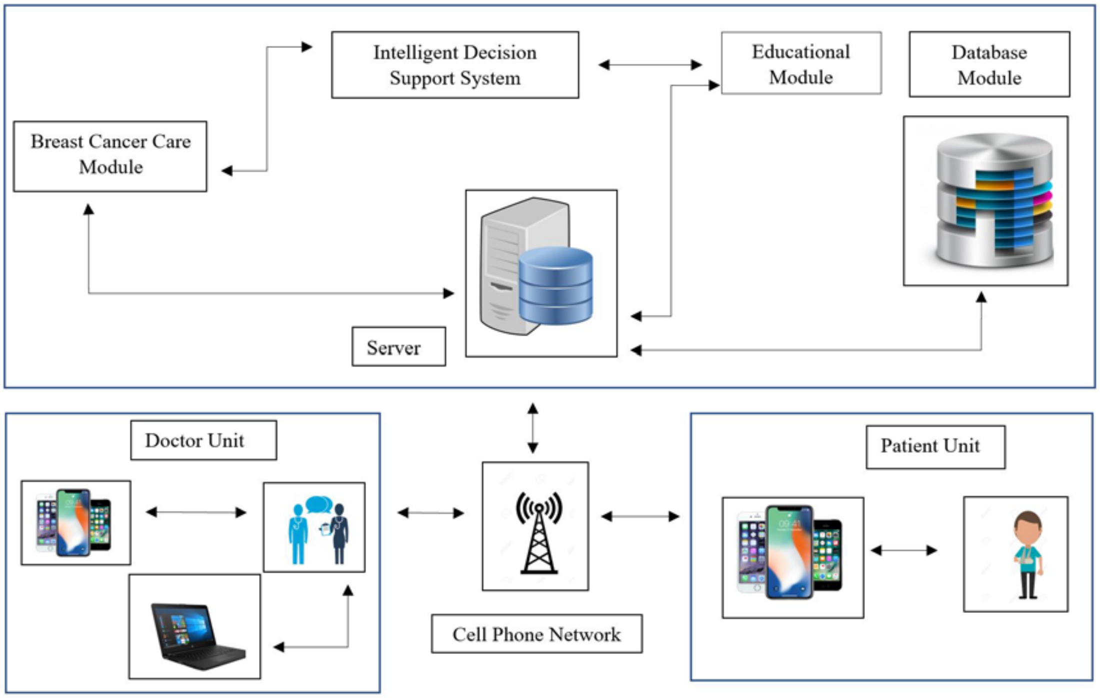

Figure 2. Description Two Components of Mobile Health Platform

Research Question #1: Does creating an M-Health platform have a positive statistically significant impact on breast cancer identification, healthcare service delivery, and recovery?

Objective #1: The objective is to create an M-health platform that can be effectively used in a rural community to support breast cancer identification, health care service delivery, and recovery.

3. Phase 2

3.1 Simulation Modeling

The second phase of the proposed research involves analyzing and interpreting the data collected from the proposed M-health platform and South African nongovernmental organizations (Cancer Association of South Africa and the Breast Health Foundation) to enhance healthcare service delivery for breast cancer patients in South Africa. The main tool that will be employed to analyze and interpret the data will be a simulation model.

A simulation model is a computer representation of a real-world system. Simulation models can be classified using three descriptors. A simulation model can be described as either static or dynamic. The key difference between these types of models is that a dynamic simulation model depends on time whereas a static model lacks this time dependency. A second descriptor used to classify simulation models is whether the models are deterministic or stochastic. Stochastic models are random in nature, and deterministic models do not have this random component. Lastly, a simulation model can be labeled as either discrete or continuous. A discrete simulation model is one where the state variables (important metrics of the system) change at a countable (or countably infinite) number of times. Conversely, a continuous system can change its state variables continuously (infinitely) over time. For this proposed research, we will only consider dynamic stochastic discrete simulation models. These types of models are commonly referred to as discrete event simulation models. Simulation modeling has seen an increase in attention and usage over the last few decades. This increase is a direct result of the availability of affordable yet powerful computers. The rapid ascension of simulation modeling was noted by Gartner (the world's leading information technology research and advisory company) when they proclaimed actionable analytics, which includes simulation modeling, as one of top ten strategic technologies in 2013. Simulation modeling has been utilized and benefited several different industries. These industries include telecommunications, airports, call centers, manufacturing, military, and the criminal justice system. So, why is simulation useful? Hagan and Dowd (2013) describe the core of simulation as "an empirically based analytic exercise of 'what if.' What if we implemented a specific public health care policy?" (p. 683). The inherent beauty of simulation is that it provides decision makers evidence-based insights even in the absence of real-world data not readily available (Seibert, 2003). Due to this reasoning, the healthcare industry is an ideal domain for the application of simulation modeling.

There has been significant research on the use of simulation models in the healthcare arena. Particularly, there have been several studies that examined how simulation could be used to improve efficiency in emergency departments. Sinreich and Marmor (2005) discussed how simulation modeling could be used as a tool for analyzing the performance of emergency departments. Oh et al. (2016) used a simulation model to improve throughput in an emergency department in Florida. This study was notable for its scope, the emergency department studied was the busiest single site emergency department in the state of Florida with over 170,000 visits in 2012, and because of the implementation of the simulation. According to the authors, "although there are many simulation based studies, very few successful implementations have been reported." Pitt, Monks, Crowe, & Vasilakis (p. 1, 2016) further validated these sentiments by remarking that "despite growing interest, serious and widespread use of systems modeling and simulation in healthcare remains limited." After implementing the changes suggested by the simulation data, Oh et al. determined the emergency department saw a 30% improvement in the average patient length of stay and 81% of patients having a length of stay in the emergency department of less than three hours. In addition to being used to assess emergency departments, simulation modeling has been used throughout the healthcare arena. Vahdat et al. (2017) used discrete event simulation to analyze the migration of separate health clinics into a single facility. Through the simulation, the researchers were able to identify congestion of patient flow that may have gone undetected otherwise. The simulation also allowed the authors to observe the effects of implementing a real-time location system technology in the new facility to address the concerns of congestion. For an extensive review of the application of discrete event simulation models in healthcare clinics, please see Jun et al. (1999). A study conducted by Fone et al. (2003) identified various areas in which simulation modeling was being applied in population health and healthcare delivery. The authors found that simulation modeling was applied in the following areas: hospital scheduling and organization, infectious and communicable disease, costs of illness and economic evaluation, and screening.

This phase of the proposed research has the following research question and objectives:

Research Question #2: Can a simulation modeling approach be used effectively to analyze, interpret, and enhance healthcare service delivery for breast cancer patients in rural South Africa?

Objective #2: Develop a simulation model of AstraZeneca's Phakamisa program that will be used to effectively analyze, interpret, and enhance healthcare delivery for breast cancer patients in rural South Africa.

Objective #3: Perform optimization of the simulation model which will determine the optimal levels of the resources used in the Phakamisa program.

3.2 Model Creation

The creation and analysis of the simulation model will be carried out in two steps. The first step is the creation of a simulation model that will simulate the interaction between Phakamisa navigators and breast cancer patients in South Africa. The simulation model will be an agent-based model due to the autonomous nature of the Phakamisa navigators and breast cancer patients. Agent-based simulation models are discrete event simulation models in which the agents (Phakamisa navigators and breast cancer patients) act independently. For a discussion on agent-based modeling see Macal and North (2007). The data needed to create the model will be collected from the proposed M-health platform after its implementation and the South African nongovernmental organizations, Cancer Association of South Africa and the Breast Health Foundation. This data will be used to calculate statistical distributions (interarrival rates) that will be used in the simulation model. Possible factors (inputs) of the model include: the number of Phakamisa navigators, the use of the M-health platform or paper to record patient data, the amount of airtime allocated to Phakamisa navigator's cell phones, and the distance traveled to meet a patient. The responses (outputs) of the model will be the average utilization rate of Phakamisa navigators and the monthly average number of people impacted by the Phakamisa navigators (see Figure 3). The simulation model will be validated by decision-makers to ensure the simulation accurately models the Phakamisa program.

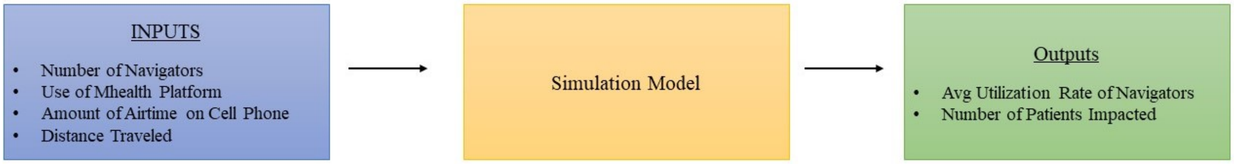

Figure 3. Description of Phakamisa Simulation Model

The data collected from the M-health platform and South African nongovernmental organizations, will also be analyzed to determine which factors are significant. Significant factors are the inputs that have the greatest effect on the response variable. Each response variable (navigator utilization and the number of patients impacted) could have a different set of significant factors. Also, it will be determined if there is any interaction between the factors. For example, calculating the interaction effect could answer the question does the airtime we allot to the Phakamisa navigators affect the number of navigators we should send out in the field? The interaction effect will be computed using sensitivity analysis and a factorial designed experiment. Sensitivity analysis involves perturbing the factors and observing if there are any significant changes in the response variables. Factorial experiments are often used as a factor screening to determine significant factors. Identifying significant factors can help decision-makers in determining where to invest their resources.

3.3 Optimization of Simulation Model

The last step involves performing an optimization of the simulation. The optimization will depend on necessary constraints. The primary goal of the optimization will be maximizing the number of patients impacted by the Phakamisa program. A secondary goal of the optimization will be maximizing the average utilization rate of the Phakamisa navigators. A metaheuristic method such as the tabu search will be used to determine the best-case scenario of the factors. This best-case scenario will provide decision makers with a recommended resource allocation. For a review of the various methods used in simulation optimization, readers are encouraged to see Fu et al. (2005). By optimizing the simulation model, the proposed research is supporting AstraZeneca's Phakamisa goal of increasing access to healthcare services.

4. Conclusion

Delivering effective healthcare to breast cancer patients is challenging especially in developing countries such as South Africa. In this paper, research is presented to help support AstraZeneca's Phakamisa health initiative. The proposed research will be delivered via two phases. The first phase involves the development and implementation of a mobile health platform. The second phase consists of the creation of a simulation model. While the implementation of a mobile health platform and simulation modeling have been studied extensively separately, there has been very little research on the effects of using both strategies simultaneously. Not only would the proposed research contribute to the body of knowledge, but it could potentially provide a helping hand to AstraZeneca in their efforts to reach their goal of impacting 3.5 million South African women by 2021.

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