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An M-Health Tool for Improved Self-Care of Heart Failure Patients: An On-Going Field Study

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AN M-HEALTH TOOL FOR IMPROVED SELF-CARE OF HEART FAILURE PATIENTS: AN ON-GOING FIELD STUDY

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ABSTRACT

This paper describes an on-going field study to develop an eHealth and mHealth system to accurately monitor heart failure and guide appropriate actions. We describe the foundations of the tool to nurture appropriate self-care behaviors along with the theoretical development to serve as the foundation. The on-going research and research design is explained in detail and implications are discussed. Preliminary data collection and descriptive analysis are presented and on-going research plans are discussed. The research will develop and test the impact of the system on the quality of care for patients, the care processes for caregivers and presents implications for the cost of care. The research is guided by the hypothesis that the mHealth tool will impact the health care provider by reducing emergency department visits and same cause readmissions – both factors that significantly impact the cost and quality of care.

Keywords

e-Health/m-Health, Heart Failure self-care, Data Analytics, Patient Activation

INTRODUCTION

Heart failure is a chronic disease that requires consistent monitoring patients' health conditions and clinical symptoms, such as shortness of breath and abrupt weight gains, to maintain patients' quality of care and manage costs. Patients with chronic heart failure need to be actively engaged in managing their health conditions. They need to understand their symptoms and take appropriate actions to manage their condition and increase their life expectancy and quality of life. Any single sign of heart failure may not be an indicator of a serious alarm, while a combination of these symptoms may lead to severe health problems or death (Chamberlain, Manemann, Dunlay, Spertus, Moser, Berardi, and Roger, 2014). Moreover, Heart Failure is a complex disease that is different for each individual. Therefore, accurate monitoring of symptoms on a daily basis and accurate identification of the heart failure condition is critically important for the patient's well-being.

BACKGROUND AND RELATED RESEARCH

Managing and reducing costs while improving quality is a perennial challenge that information systems have focused on, in both traditional management areas and more recently in healthcare (Helm, Ahmad Beygi and Van Oyen, 2011; Theokary and Ren, 2011; Helm, Alaeddini, Stauffer, Brethauer and Skolarus, 2015). In 2013 alone, the Centers for Medicare and Medicaid Services (CMS) reported that Medicare spending grew 3.4% to $585.7 billion dollars, and Medicaid spending grew 6.1% to $449.4 billion, comprising of 35% of total national health expenditures ("NHE-Fact-Sheet," 2015). Much research attention has focused on the development and application of specific analytics to support intelligent clinical and operational decision making in the healthcare domain. Healthcare organizations face increasing pressures to improve the quality of care and deliver improved clinical outcomes while simultaneously reducing the costs of care provided. This is a very challenging task that many healthcare organizations are facing.

The affordable care act holds healthcare providers accountable for the quality of care delivered by managing reimbursements for services based on measures of the quality of service provided against established standards. Moreover, the Centers for Medicare and Medicaid Services (CMS) explicitly implements programs to continually improve standards. This further increases the pressure on hospital systems and healthcare providers. For example, in

2012, CMS implemented the hospital readmissions reduction program by which payments would be reduced for hospitals with "excessive" readmissions in 30-days. This was judged against an average benchmark for common but significant conditions such as a heart attack, heart failure or chronic obstructive pulmonary disease (COPD). Similar programs such as the hospital acquired condition reduction program, under the inpatient prospective payment system (IPPS) regulations and notices create significant financial interventions, including incentives and disincentives, for hospitals and healthcare systems to manage costs, improve quality and provide better care - simultaneously. This presents the challenge for today's healthcare environment to meet continually increasing standards of care while meeting more exacting cost standards.

DESIGNING ANALYTICS-BASED INTELLIGENT DECISION SUPPORT FOR HEART FAILURE PATIENTS

In healthcare literature, one of the most prominent themes is addressing the dual objectives of cost and quality (Berwick, Nolan, & Whittington, 2008; Ma, 1994; The White House, 2013; Weisbrod, 1991). Healthcare organizations are increasingly interested in knowledge-driven decision analytics to improve decision quality and the decision support environment. This requires use of corporate data to develop higher-level knowledge in conjunction with analytical tools to support knowledge-driven analysis of business problems (Ba et al., 1997). The Patient Protection and Affordable Care Act of 2010, encourages care providers to make data available to researchers in an effort to motivate research that improves the quality and reduces the cost of care. ACA requires that all hospitals implement electronic medical record (EMR) technologies. In doing so, the ACA creates an opportunity for researchers to identify utility from patterns and relationships hidden in health care data. Advances in systems support for problem solving and decision-making increasingly use artificial intelligence (AI) based techniques to identify knowledge and for knowledge representation (KR) (Whinston, 1997; Goul and Corral, 2005). KR may take multiple forms including business rules, decision analytics and business intelligence generated from various machine learning algorithms and data mining techniques. *Intelligence is the ability to act appropriately in an uncertain environment to increase the probability of success and achieve goals* (Albus, 1991). For systems, acting with intelligence requires knowledge. Designing intelligent decision support requires gathering and incorporating intelligence from the problem domain to inform and support the decision process in a manner that improves outcomes and engages the decision maker in better informed decision making.

Design is the use of scientific principles, technical information and imagination in the definition of a system. "Design science addresses research through the building and evaluation of artifacts to meet the identified business need. The goal of design research is utility" (Hevner, et al., 2004). Design science improves the understanding of a problem domain by developing purposeful IT design artifacts that address important organizational problems. These innovations define the ideas and technical capabilities useful to develop systems for the problem domain. The design artifact includes the construct vocabulary and symbols, models that provide abstraction and representations, methods and prototype instantiations that illustrate proof-of-concept for evaluation (Hevner, et al., 2004; March and Smith, 1995). Research in systems makes a contribution by utilizing systems domain knowledge and problem domain knowledge to develop better artifact for the problem domain, thereby improving the state of the art in the problem domain (Khatri, et al., 2006). This, in turn improves our ability to design better systems (March and Smith, 1995). The overall objective of this research is to investigate the *purposeful* use of predictive and explanatory analytics in engaging patients in their self-care and study the impact of these mechanisms on the cost and quality of care for patients with Heart Failure.

APPLYING ANALYTICS TO IMPROVE SELF-CARE OF HEART FAILURE THROUGH MHEALTH

Chronic heart failure refers to the ongoing condition when the heart is unable to pump sufficient blood to meet the body's demands. A medical condition that includes the word "failure" can be intimidating to patients, but patients can identify ways to increase the chances of living longer and living well with HF. Sears et al (2013) note that *to live successfully with HF, it is important to develop confidence*. This confidence includes self-assurance, positive and healthy actions and the expectation that desirable health outcomes are achievable. This confidence can be achieved through effective self-care in managing the HF condition. This includes a level of understanding about the medical condition, knowing what symptoms to monitor and making informed decisions about self-care to respond effectively to symptoms.

The motivating hypothesis of this study is that mHealth systems can be designed to improve and guide self-care activities of patients and help them engage and achieve the self-confidence necessary for effective self-care. mHealth refers to the practice of medicine and public health supported by mobile devices, including smartphones, and tablets. Moreover, they provide the opportunity to deliver very specific individualized health and educational interventions focused for each individual patient. We argue that these interventions can be informed by knowledge generated from analytics developed based on healthcare data.

Specifically,

> *We propose that Patient self-care behaviors and awareness of their condition can be improved by using mHealth tools, in order to increase patient activation and improve their quality of care.*
>
> *In addition, we propose that the quality, accuracy and communication of information involved in clinical diagnoses can be improved using mHealth Tools, in order to increase the quality of care and reduce costs.*
>
> *The health system benefits from the use of the mHealth tool by improvements in the cost of care and the quality of care provided to its patients, as evidenced by fewer readmissions.*

The study is motivated to employ effective analytics to design such interventions and investigate the impact on these critical issues.The extant literature provides guidance to develop the research model outlined in figure 1.

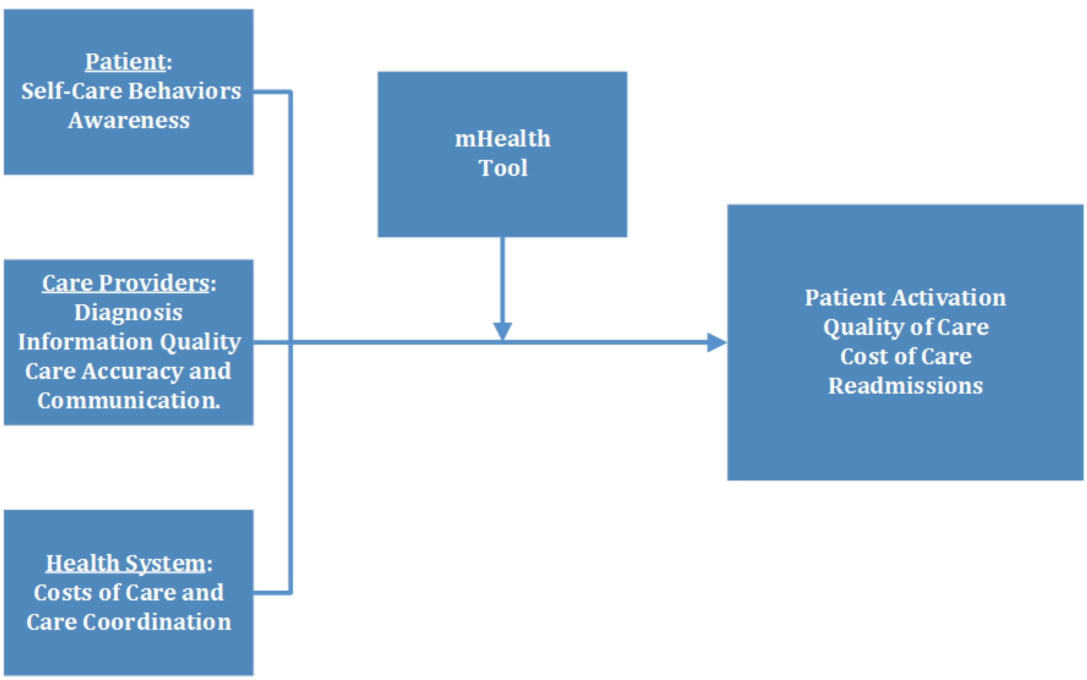

Figure 1: Conceptual Research Model.

METHOD

This study will be implemented in three stages, shown in figure 2, and described in further detail in the sections that follow.

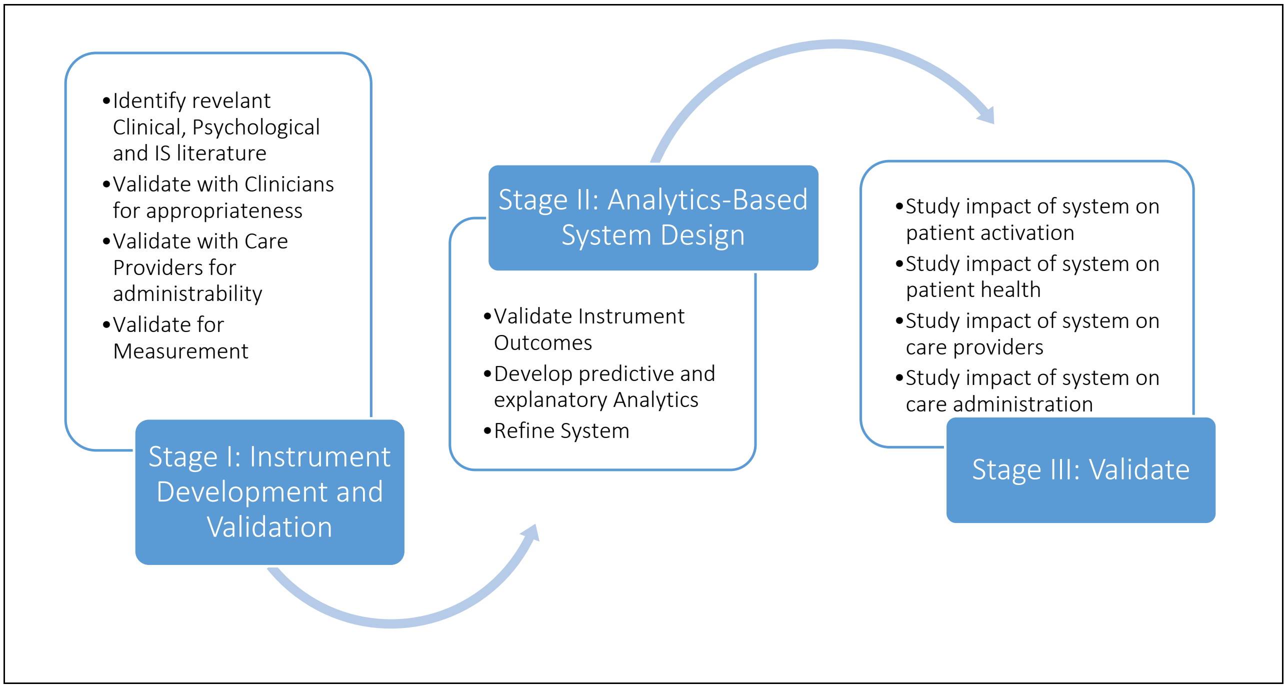

Figure 2: Research Design to develop an Analytics-Based m-Health System for improved self-care of Heart Failure Patients

Stage 1: Instrument Development

The first stage will be dedicated to identifying the critical symptoms as the indicators of the level of severity of the patient's health condition. The psychometric properties of the symptoms will be identified (Reigel, Carlson, Moser, Sebern, Hicks, and Roland, 2004) and the instrument will be validated using the uni-dimensional Rasch measurement approach. The clinical literature provides multiple well-established studies to guide the development of educational materials and self-care mechanisms for patients with heart failure. Reigel and Dickson (2008) put forward a situation-specific theory of heart failure self-care. Rahimi et al (2014) provide a comprehensive review of the literature of risk prediction for heart failure and identify the most consistently reported independent predictors of risk across models of heart failure. They note that despite recent advances in diagnosis and management, average outcomes in patients with heart failure remain poor and highly variable. In calling for further research on the nature and quality of post-discharge care, Fischer et al (2015) note that it is unclear whether in-hospital quality of care is the key determinate of readmission or whether readmissions are likely influenced more by post-discharge care, including self-care factors. In their study on the impact of social factors on risk of readmission of HF, Calvillo-King et al (2012) find that a broad range of social factors impact the risk for the HF patient and call for more research on identification of such factors. The Minnesota Living with Heart Failure questionnaire (MLHF) was designed in 1984 to measure the effects of heart failure and treatments for heart failure on an individual's quality of life. Reigel defines self-care as a naturalistic decision-making process that influences actions that maintain physiologic stability, facilitate the perception of symptoms, and direct the management of those symptoms. The first self-care process is maintenance, which captures treatment adherence and healthy behaviors (e.g., taking medications, exercising, and following a salt restricted diet). The second self-care process, symptom perception, involves both the detection of physical sensations and the interpretation of meaning. Specifically, symptom perception involves body listening, monitoring signs, as well as recognition, interpretation, and labeling of symptoms. Individual symptoms and the interactions between symptoms influence the meaning attributed to the symptom experience. The third self-care process is management, or the response to symptoms when they occur. (Reigel, et al, 2015). We utilized these and multiple additional theories on self-determination and self-efficacy to develop the instrument.

At this stage of the research, we have developed and implemented the instrument and are in the process of validating the measurement by collecting data at a local cardiovascular clinic. The following stages provide the reader with the plan of action for this research in progress. We expect to share preliminary results at the conference.

Stage 2: Analytics Development and System Refinement.

The second stage of the study will be allocated to design an adaptive measurement instrument based on the patient's' historical health information using the results of explanatory and predictive analytics. It is noteworthy that the analytics will be applied to the data collected from Stage I as well as EMR and other health system data on the cost and quality of care for HF patients. We will apply the machine learning algorithms to understand the historical health conditions of patients and predict the outcomes of patients. Specifically, explanatory analytics make particular impact in helping users understand, interpret and utilize the results of analytics in making decisions and solving problems. The explanatory power afforded by decision trees comes from generation of understandable rules, clear identification of fields that are most important for prediction and classification and the incorporation of explanation facility. Explanation is essential to the interaction between users and knowledge-based systems (KBS) describing what a system does, how it works, and why its actions are appropriate (Mao and Benbasat, 2000). Explanation can make KBS conclusions more acceptable (Ye and Johnson, 1995) and build trust in a system (Swartout, 1983). Decision trees lend themselves to automatic generation of structured queries to extract pertinent data from organizational data repositories making them particularly useful in providing insights and explanations for the non-technical user (Apte and Weiss, 1997). Decision trees are especially suitable for decision problems that require generation of human understandable decision rules based on a mix of classification of categorical and continuous data (Quinlan, 1996). They clearly indicate the importance of individual data fields to the decision problem and reduce the cognitive burden of the decision maker (Mao and Benbasat, 2000). Decision trees represent a powerful and easily interpretable technique for modeling business decisions that can be reduced to a rule-based form. We will assess the significance of individual measures in explaining and predicting the progress of the patient's health condition. Multiple instruments provide complementary measures of heart failure. Little research has determined the combined value of measures in explaining the disease condition progress and developed systematic decision support mechanisms to monitor and manage this health condition. In the second stage, our research evidence will be used to customize mHealth interfaces with the appropriate measurement models to offer the unique customized mix that patients need.

Stage 3: System Validation and Impact Testing

The third stage of the study will conduct a randomized trial to study the influence of this system as an intervention to enhance patient engagement and the improvements in the quality and cost of care. Our guiding hypothesis is that the implementation of this system will improve the quality of care for patients through daily monitoring of their heart failure symptoms and provide appropriate signals for action for doctors and care providers. Specific propositions to be tested were described earlier, following the research model presented in Figure 1. These hypotheses will be tested through comparison of quality of care and cost of care measures before and after implementation of this system as an intervention.

CONCLUSION AND ON-GOING RESEARCH

Accurately informed self-care behaviors have significant impact on the quality of care and the health outcomes for patients with chronic disease conditions, particularly Heart Failure. This has direct impact on the cost and quality of care that a health system is able to provide for its patients. Heart Failure is a complex disease that is different for each individual. mHealth technologies offer the opportunity to deliver very specific and personalized health and educational interventions for each individual patient. This paper describes an on-going research study to design such a specific mHealth tool using knowledge generated from explanatory and predictive analytics using healthcare data. We argue that such systems can be designed to improve and guide self-care activities of patients and help them engage and achieve the self-confidence necessary for effective self-care. The paper describes the research design to develop, test and validate such mHealth tools to improve the quality and cost of care for HF patients. We hope to share preliminary findings of our research at the conference.

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REFERENCES

1. Albus, J. S. (1991) "Outline for a Theory of Intelligence". *IEEE Transactions on Systems, Man, and Cybernetics*. Vol. 21, No. 3, May/June.
2. Apte, C.,Weiss, S. (1997) "Data mining with decision trees and decision rules" *Future Generation Computer Systems* (13) pp. 197-210
3. Calvillo–King, L., Arnold, D., Eubank, K. J., Lo, M., Yunyongying, P., Stieglitz, H., & Halm, E. A. (2013). Impact of social factors on risk of readmission or mortality in pneumonia and heart failure: systematic review. *Journal of General Internal Medicine*, 28(2), 269-282.
4. Chamberlain, A. M., Manemann, S. M., Dunlay, S. M., Spertus, J. A., Moser, D. K., Berardi, C. & Roger, V. L. (2014) "Self-Rated Health Predicts Healthcare Utilization in Heart Failure." *Journal of the American Heart Association*, vol 3(3) e000931.
5. Fischer, Claudia, et al. (2015) "A systematic review and meta-analysis on the association between quality of hospital care and readmission rates in patients with heart failure." *American heart journal* 170.5: 1005-1017.
6. Helm, J. E., AhmadBeygi, S., & Van Oyen, M. P. (2011). Design and analysis of hospital admission control for operational effectiveness. *Production and Operations Management*, 20(3), 359-374.
7. Helm, J. E., Alaeddini, A., Stauffer, J. M., Bretthauer, K. M., & Skolarus, T. A. (2015). Reducing hospital readmissions by integrating empirical prediction with resource optimization. *Production and Operations Management*.
8. Hevner, A., March, S.T., Park, J., and Ram, S. (2004) "Design Science Research in Information Systems," *MIS Quarterly* (28:1), pp. 75-105.
9. Khatri, V., Vessey, I., Ramesh, V., Clay, P., Park, S., (2006) "Understanding Conceptual Schemas: Exploring the Role of Application and IS Domain Knowledge", *Information Systems Research*, Vol. 17 Issue 1, pp., 81-99
10. Mao, J., Benbasat, I., (2000) "The Use of Explanations in Knowledge-Based Systems: Cognitive Perspectives and a Process-Tracing Analysis", *Journal of Management Information Systems*, 17:2 153-179
11. March, S. & Smith, G.F. (1995) "Design & natural science research on information technology" *Decision Support Systems*, 15, 251–266.
12. Quinlan, J. R., (1996) "Learning First-Order Definitions of Functions", *Journal of Artificial Intelligence Research*, 5. 139-161
13. Rahimi, K., Bennett, D., Conrad, N., Williams, T. M., Basu, J., Dwight, J., ... & MacMahon, S. (2014). Risk prediction in patients with heart failure: a systematic review and analysis. *JACC: Heart Failure*, 2(5), 440-446.
14. Riegel, B., Carlson, B., Moser, D. K., Sebern, M., Hicks, F. D. & Roland, V. (2004) "Psychometric testing of the self-care of heart failure index." *Journal of cardiac failure*, vol 10(4), pp.350-360.
15. Riegel, B., Lee, C. S., Dickson, V. V. & Carlson, B. (2009) " An update on the self-care of heart failure index." *The Journal of cardiovascular nursing*, vol 24(6), p.485.
16. Theokary, C., & Justin Ren, Z. (2011). An empirical study of the relations between hospital volume, teaching status, and service quality. *Production and Operations Management*, 20(3), 303-318.
17. Whinston, A.B. (1997) "Intelligent Agents as a basis for Decision Support Systems", *Decision Support Systems*, 20:1.
18. Ye, L.R., Johnson, P.E. (1995) "The impact of explanation facilities on user acceptance of expert systems advice". *MIS Quarterly*, 19:2, 157-172.