MIRZAEI, TALA, Ph.D. Investigating the Impact of Health Analytics on the Cost and Quality of Care for Patients with Heart Failure. (2016)
Directed by Dr. Rahul Singh. 143 pp.

The healthcare industry is under tremendous pressure to improve the quality of care and provide more patient centric care, while reducing costs. The potential use of data analytics to address these health system issues has raised significant interest in both research and practice. Health Analytics is central to informing and realizing the systematic quality improvements and cost reductions required by healthcare reform. Fundamentally, the contribution of IS and analytics research in healthcare is to identify and study the impact of interventions that can make a significant difference to the quality and cost of care.

This dissertation is concentrated on patients with heart failure (HF). HF is the number one killer in the world, and is the largest contributor to healthcare costs in the United States. Moreover, HF is one of the six conditions used by the Centers for Medicare and Medicaid Services (CMS) to exercise fiduciary control over health systems by monitoring both the quality and cost of care. Specifically, my larger research question is "*How can we identify and inform impactful transition of care interventions that manage costs and improve resource allocation efficiencies while providing improved quality of care for heart failure patients?*" We adopted a mixed-method approach to study the impact of transitional care in a healthcare system for patients with heart failure.

This dissertation includes three essays. In the first essay, I use qualitative methods to study the nature, sources and impacts of information coordination problems as HF patients' transition through the patient flow in a health system. I propose a set of interventions based on my analysis of information and control errors along the continuum of care to inform the design of appropriate interventions that improve the cost and quality of care. In the second essay, I empirically evaluate the impact of these interventions on cost and quality of care measures such as all cause readmissions, heart failure readmissions, ER visits, length of stay, and cost of care. Analysis suggests that multicomponent complex transitional interventions have significant impact on reducing 30-day readmission and ER visits. The third essay is dedicated to understanding the impact of heart failure patient's self-care behaviors. I developed and validated an assessment tool for patients with heart failure to monitor and score their condition accurately. Together, these essays investigate impactful transition of care interventions that can help healthcare organizations improve quality of care and manage costs from the clinical, administrative and patient perspectives.

INVESTIGATING THE IMPACT OF HEALTH ANALYTICS

ON THE COST AND QUALITY OF CARE FOR

PATIENTS WITH HEART FAILURE

by

Tala Mirzaei

A Dissertation Submitted to
the Faculty of The Graduate School at
The University of North Carolina at Greensboro
in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Greensboro
2016

Approved by

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To the loving memory of

Pary

and

Mehrdad Khorrami

APPROVAL PAGE

This dissertation written by TALA MIRZAEI has been approved by the following committee of the Faculty of The Graduate School at The University of North Carolina at Greensboro.

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ACKNOWLEDGEMENTS

I would like to acknowledge the support and encouragements that I received from several individuals for this research: The Chair of my dissertation committee, Dr. Rahul Singh, who is the best mentor, colleague and friend I could have hoped for. Dr. Daniel Bensimhon, who has generously shared his expertise and guidance about coordination of care for patients with heart failure. This research is supported by the Health Technology Initiative at The Bryan School of Business and Economics which was made possible through the support of Dr. Kathy Loyd. I would like to thank Dr. Terry Ackerman who have always provided invaluable advises and I was not a graduate student without his support. Special thanks to my family for their unconditional love and support throughout my journey.

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CHAPTER I

INTRODUCTION

1.1. Introduction

The healthcare industry undergoes increasing regulatory and policy pressures to improve the quality of care while maintain costs. The affordable care act holds healthcare providers accountable for the quality of care delivered by managing reimbursements for services based on measuring the quality of service provided against established standards. Moreover, the Centers for Medicare and Medicaid Services (CMS) is explicitly implementing programs that are aimed to continually improve standards, thereby increasing the pressure on hospital systems and healthcare providers. Section 3025 of the Affordable Care Act, which established the hospital readmissions reduction program, requires that CMS reduce payments to hospitals with excess readmissions, effective for discharges beginning on October 1, 2012 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 implement significant financial interventions, including incentives and disincentives, that requires hospitals and healthcare systems to manage costs, improve quality and provide better care simultaneously.

These represent the challenge for today's healthcare system environment to achieve continually increasing standards of care while meeting more exacting cost standards.

Much current research is focused on improving clinical and administrative efficiency, quality of care, affordability and cost of care and fee-for-value. Health Analytics is central to informing and realizing the systematic quality improvements and cost reductions that are required in today's healthcare environment. The mass adoption of electronic medical records (EMR) and proliferation of data on health outcomes and claims provide a unique opportunity for researchers to investigate health analytic techniques to identify and assess impactful interventions and predict potential trends in patients' health outcomes and costs. Research in analytics has the potential to enhance the functionality and productivity of healthcare systems by improving healthcare quality while reducing costs (Bardhan and Thouin 2013, Das, Yaylacicegi, & Menon, 2011). Several recent studies (eg. Agarwal, Gao, DesRoches, & Jha, 2010) recognize the need to identify ways that measure and quantify the impact of health information technology (HIT) and call for more research on how IS can affect positive outcomes on patient care, improve efficiencies and manage costs.

Much research attention has focused on the application of information and management science techniques to identify systematic interventions that can reduce random and uncontrolled variability in demand by managing uncertainty. For example, Jack and Powers (2004) developed a research framework to study the highly dynamic and uncertain demand characteristics that health services face. They investigate volume flexibility as a strategy for healthcare organizations to improve the services they deliver in a manner that uses their scarce resources effectively to meet random and uncontrolled demand. Several studies investigate the levels of variability in demand for health services (eg. Salzarulo, Bretthauer, Cote and Schultz, 2011) and emphasize the need to study and reengineer healthcare system to better optimize allocation of resources and control costs, while improving the impact on population health and patient satisfaction (Venkat, Kekre, Hegde, Shang and Campbell, 2015). One key determinant of healthcare recourse utilization and capacity management to improve hospital operations is controllable patient flow (Huang, Carmeli, & Mandelbaum, 2012). Patient flow refers to the flow of patients through the healthcare delivery process and is identified as a central driver of a hospital's operational performance (Armony, Israelit, Mandelbaum, Marmor, Tseytlin, &Yom-Tov, 2015). Patient flow management is strongly associated with the overall quality and cost of healthcare (Pitts et al. 2008, Niska et al. 2010).

A systematic review of these studies underscore the importance of the question: how can we develop and study the impact of innovative management interventions to reduce or manage demand uncertainty, improve the efficiency and effectiveness of resource allocations and resource utilization, while at the same time meet the challenge of providing improved quality of care for patients to meet the demands of external regulatory and insurance agencies. This question has a very large scope. Thus, the research runs the risk of being vague and dispersed and losing utility. In order to maintain the value and relevance of the research, this dissertation is focused on Chronic Heart Failure (HF).

Chronic heart failure refers to the ongoing condition when the heart is unable to pump sufficient blood to meet the body's demands. HF is the number one killer in the world, more than cancer, and is the largest contributor to healthcare costs in the United States (AHRQ, 2008; CDC, 2011). Moreover, it is one of the six conditions used by the Centers for Medicare and Medicaid Services (CMS) to exercise fiduciary control over health systems by monitoring readmissions - a measure of both the quality and cost of care. In this dissertation, I focus on identifying and assessing impactful interventions for improving the quality and cost of care for patients diagnosed with chronic heart failure.

The clinical literature identifies transitional care programs as a complementary approach to manage demand uncertainties while improving the quality of care provided. Transitional care refers to actions designed to coordinate the continuity of healthcare as patients transfer from one care facility to another. Stamp, Machado and Allen (2014) provide an integrative review of the clinical impact of transitional care programs on heart failure patients. However, there is little research that investigates the impact of transitional care programs on health care systems from an operations perspective. Recognizing the importance of this need, the American Heart Association issued a scientific statement in 2015 (Albert et al, 2015) calling for research on heart failure transition care to identify best practices that ensure economically and clinically effective and feasible transition clinics.

Improved systems support for transitions in the continuum of care impacts the cost and quality of care and saves patient lives. This dissertation investigates impactful interventions for patient with chronic heart failure that can affect the quality and cost of care along the continuum of care from the clinical, administrative and patient perspectives. This dissertation comprises three essays. The first essay uses qualitative research methods to analyze the operational workflow of heart failure patients along the continuum of care to identify clinically feasible and administratively viable transitional care interventions. The second essay will empirically test the impact of transitional care interventions. Using analytic techniques, I compare the impact of implementation of transition care clinic on cost and quality of care measures. The third essay is focused on design and validation of a self-care tool for heart failure patients. I develop this assessment tool as an intervention to improve the quality of care for patients with heart failure and reduce costs. These three studies contribute to the current state of knowledge about how information systems can be designed to support the care of heart failure patients along the continuum of care.

In the following section, I introduce the motivation and research gap for each essay and discuss its implications. In chapter I introduce the theoretical background to inform each essay. In chapter 3, I present the research approach and expected outcomes for each essay and provide a timeline for my progress.

1.1.1. Essay 1_ Healthcare System Coordination Network

In a healthcare system coordination network, transition of accurate and timely information from one point of care to another is critically important. The coordination of activities between care-providers are supported through the mechanism that are embedded in the health information systems. In order to provide efficient care, all care-providers along the continuum of care in a healthcare system need to have access to the right information about the patients that they visit at each point of time. They also need to be able to convey the right information about the patient's health condition and treatments to the patient themselves and the next care giver who will visit the patient through their care process. Naylor, Aiken, Kurtzman, Olds and Hirschman (2011) identify that these points of transition are areas that contribute to high healthcare costs and low quality of care and are associated with increased rates of readmission.

Interestingly, much of the current literature in information systems and operations management seems to focus on improved control and management of demands placed on the system by random and uncontrolled ingress of patient needs and characteristics into the health system. Business goals and objectives are obtained through business processes in organizations. Information resources are transitioned and exchanged through business processes within and across organization boundaries (Raghu and Vinze, 2007). A business process envisions the transition of information resources as well as the roles and responsibilities of actors among business activities in a coordination network (Singh and Salam, 2006). Business processes require coordination mechanisms to manage the interdependencies of business tasks and activities in an organization (Malone, 1990). This particularly important in a health care system to manage the flow of patients along the continuum of care.

Little research examines how these complementary mechanisms together can be used to improve patient outcomes by coordinating the ingress and egress patient flows. This essay adapts coordination theory (Malone & Crowston, 1990) to investigate the control flow errors and data flow errors (Van der Aalst, 2000; Van der Aalst, 2009) along the continuum of care for patients with heart failure. I use qualitative methods to propose a mechanism to identify effective practices applicable in the transition care clinic to improve the quality of care and reduce costs. Analysis of these multiple perspectives provide the opportunity to identify and analyze patient workflows for the coordinated care delivery through the continuum of care for the accountable care organization (ACO) patients, as well as regular patients of the heart failure clinic. Specifically, the analysis in this research will identify the roles and responsibilities of each actor and their information requirement for error free workflows in the continuum of care. This provides the opportunity to model and study the impact of introducing the transition clinic on the patient flow, the clinical workflow and the administrative workflow.

This study provides a framework to identify the control and data error flows along the continuum of care and provides the insight to identify appropriate and impactful interventions that are need to be implemented in transition care clinics for patients with heart failure. This informs a robust way of coordinating care and has desirable impact on managing the complete care continuum and on reducing readmission rates - a key operational and cost of care measure.

1.1.2. Essay 2_ Empirical Investigation of Impactful Interventions

One of the most prominent themes in healthcare literature, 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, Lang, & Whinston, 1997). The Patient Protection and Affordable Care Act (ACA) 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. The 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. Empirical validation of the clinical and administrative interventions contributes significantly in informing clinical and administrative strategies and activities to improve the quality of care and control costs.

Meyer (1995) argues that natural experiments can be improved through the use of multiple treatment and comparison groups that allow for further investigation and refinement of hypotheses. In addition, the use of multiple pre-intervention and post-intervention are suggested to validate differences and assess the influence of omitted factors. Meyer (1995) writes that "good natural experiments are studies in which there is a transparent exogenous source of variations in the explanatory variables". He includes that the main lesson of these studies is the emphasis on understanding sources of variation that are used to estimate key parameters through the difference-in-differences approach. Bertrand, Duflo and Mullainathan (2002) provide guidelines and constraints on drawing appropriate inferences from the difference-in-differences approach. Puhani (2012) notes that difference-in-differences estimation is one of the most important identification strategies in applied economics when studying the impact of a single treatment. The association between policy implementation and outcomes is estimated by examining the cross-difference and interactions between the pre-post and exposed-unexposed variables (Puhani, 2012). Recently, in the Journal of the American Medical Association Guide to Statistics and Methods, Dimick and Ryan (2014) note the utility of the difference-in-differences approach to observational field studies that investigate the association between policy interventions and subsequent changes in explanatory variables, while accounting for background changes in outcomes that occur with time or other endogenous variables.

The second essay applies the cost and quality measures identified in the first essay and presents an in-depth multi-method research investigation into the feasibility and design, as well as the impact of transitional care on the quality and cost of care outcomes including patient experience, clinical patient outcomes, access to care, cost of care and operational measures such as readmission rates.

The preliminary null-hypotheses include:

- *There is no significant difference on an individual's clinical measures for hospitals with transition clinic.*
- *There is no significant difference on aggregate clinical measures for hospitals with transition clinic.*
- *There is no significant difference on an individual's cost/operational measures for hospitals with transition clinic.*
- *There is no significant difference on aggregate cost/operational measures for hospitals with transition clinic.*

A novel aspect of this research is to study the impact of cost and quality of care measure on both an individual as well as an aggregate level. This study employs advanced analytics to empirically test the causal impact of transition care clinic as an intervention on patients with heart failure.

1.1.3. Essay 3_ Self-care Management for Patients with Heart Failure

Patients with chronic conditions make day-to-day decisions about their illnesses. Effective self-management interventions, such as self-monitoring and decision making, lead not only to improvements in health outcomes and health status, but also to increased patient satisfaction and reductions in hospital and emergency room costs (Bodenheimer et al., 2002). Heart failure is a chronic disease that requires consistent monitoring of patients' health conditions and clinical symptoms, such as shortness of breath and abrupt weigh gains, to improve the quality of care and manage costs. Patients with chronic heart failure need to be actively engaged in managing their health conditions (Riegel, Lee, Dickson, & Carlson, 2009). They need to understand their symptoms and take appropriate actions to 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 et al., 2014). Research suggests that poor knowledge of their health condition compromises patients' safety and is associated with poor self-care behaviors and non-compliance (Riegel et al., 2009).

Heart Failure is a complex disease that is different for each individual. Accurate monitoring of symptoms and accurate identification of the heart failure condition is critically important for the patient's well-being. 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. This opens an opportunity to investigate the contributions of patients' self-management on improving the quality of care. The research question is "*How can we develop interventions to improve, inform and activate patients' self-care behaviors leading to improvements in the cost and quality of care?*" This essay aims to design a self-administrable assessment instrument for patients with chronic heart failure.

This heart failure assessment instrument acts as a decision making tool to signal appropriate actions based on patient's scores. Multiple validated studies regarding access and utilization of healthcare, provider-patient interaction and studies on effective self-care, guide the development of preliminary methods to systematize instrument development and subsequent data collection. The study contributes to development of evidence-based clinical decision support tools which can be available on the web, mobile devices or in print for real time use in clinical setting or at home for heart failure patients. This assessment tool will guide activities of patients and help them engage and achieve the self-confidence that is necessary for effective self-care. In addition, it enables hospitals to deliver specific, individualized health and educational interventions for each patient.

1.2. Summary of Chapter I

Health Analytics is central to informing and realizing the systematic quality improvements and cost reductions required by healthcare reform. Fundamentally, the contribution of IS and analytics research in healthcare is to identify and study the impact of interventions that can make a significant difference to the quality and cost of care.

In this dissertation, I focus on the question "How can we identify and inform impactful transition of care interventions that manage costs and improve resource allocation efficiencies while providing improved quality of care for heart failure patients?" I adopt a mixed-method approach to study the transitions of information in a healthcare system and investigate impactful transition of care interventions that can help healthcare organizations improve quality of care and manage costs from clinical, administrative and patient perspective.

CHAPTER II

THEORETICAL BACKGROUND AND LITERATURE REVIEW

In this chapter, I introduce the theoretical background that I adapt for this dissertation. I employ a mixed method using both qualitative and quantitative techniques. The qualitative approach identifies concepts, relationships and sources of error that reveal opportunities to identify impactful interventions from the perspective of administrators and care providers in a healthcare system. The impact of these approaches are tested using quantitative techniques with a natural experimentation design. Having studied the phenomena of transitional care for heart failure patients from both the care provider and administrators' perspectives in essays 1 and 2, I then study the role of patients and they can contribute to improvements in cost and quality of care by engaging in well-informed self0care behaviors. Taken together these provide a holistic perspective on the concept of transitional care for patients with heart failure along the continuum of care.

In the following I introduce the mixed method approach and provide the reader on the perspective on how different methodologies can be engaged in a complimentary mechanism to reveal a more complete picture of a phenomenon. I then introduce the reader to a theoretical background of the central theories and concepts employed in my research. This is intended to provide the reader with an overall view of my research and familiarize the reader with the essential theoretical background.

2.1. Mixed Methods Research

Mixed methods research, uses quantitative and qualitative research methods, either concurrently (i.e., independent of each other) or sequentially (e.g., findings from one approach inform the other), to understand a phenomenon of interest. Proponents of mixed methods research appreciate the value of both quantitative and qualitative worldviews to develop a deep understanding of a phenomenon of interest. For example, a researcher may use interviews (a qualitative data collection approach) and surveys (a quantitative data collection approach) to collect data about a new phenomenon. Creswell and Clark (2007) suggested four major types of mixed methods designs: (1) triangulation (i.e., merge qualitative and quantitative data to understand a research problem); (2) embedded (i.e., use either qualitative or quantitative data to answer a research question within a largely quantitative or qualitative study); (3) explanatory (i.e., use qualitative data to help explain or elaborate quantitative results); and (4) exploratory (i.e., collect quantitative data to test and explain a relationship found in qualitative data). Other researchers proposed different typologies of mixed methods research with respect to the temporal sequence of data collection and analyses (Morse 2003; Teddlie and Tashakkori 2009). Regardless of the type of research design employed, the key characteristic of mixed methods research is the sequential or concurrent combination of quantitative and qualitative methods (e.g., data collection, analysis and presentation) within a single research inquiry.

Venkatesh, brown and bala (2013) elaborate on three important aspects of conducting mixed methods research: (1) appropriateness of a mixed methods approach; (2) development of meta-inferences (i.e., substantive theory) from mixed methods research; and (3) assessment of the quality of meta-inferences (i.e., validation of mixed methods research). They suggest that IS research can benefit from this research approach, especially with a broadening base of interdisciplinary research and calls for more of the same.

This dissertation is designed based on mixed method approach. The first study adapts qualitative techniques to identify impactful interventions for patients with heart failure that contribute to better quality of care and reduction in costs. The second essay adapts quantitative techniques to empirically test the impact of those interventions that are identified by the first essay on quality and cost of care measures. The third essay adapts both qualitative and quantitative techniques to develop and validate an assessment instrument for self-care management of patients with heart failure. Together these three essays provide a holistic view of impactful interventions embedded in information systems to improve the quality and cost of care for patients with chronic heart failure.

2.2. Coordination Theory

Information systems are ubiquitously applied in organizations to facilitate business processes by coordinating the activities of various groups of employees in a more efficient and effective manner. To achieve this goal, the resources and information that are required to perform an activity need to be readily available for the employees to deliver their responsibilities more accurately and in a timely fashion. A key issue that contributes to managing activities in a business process is an understanding of the dependencies between the tasks that different group members are carrying out and the way they coordinate their work.

Coordination theory (Malone and Crowston, 1994) describes an approach to investigate the interdependencies between different activities in a group. They explain coordination theory as a body of principles about how activities can be coordinated so that actors can work together harmoniously to achieve the common goals of the group. Coordination problems are common across a variety of disciplines. Malone and Crowston (1990; 1994) provide several examples of problems and issues that arise due to poorly managed interdependencies among activities in a group. For instance, approaches to share a resource between multiple tasks that require the same resource have been studied in economics, organization theory and computer science. Other dependencies include controls and constraints between different tasks and subtasks relations. Coordination theory provides a set of principles to address these problems.

In the context of healthcare systems, coordination between the activities of the care-providers and transition of resources and information from one point of care to another is significantly important. I use coordination theory to study the transition of information along the continuum of care for patients with heart failure form the time they enter the health system to the point of discharge. This allows the identification of potentially impactful interventions which may lead to better quality of care and reduce costs.

2.3. Workflow Management Systems

Process management and process automation is critically important for any organization to be able to deliver effective and efficient services. Management of business processes in an organizational setting is referred to as workflow management. Information systems that embed management processes are called workflow management systems (Van der Aalst, 1996). Database systems are being extended to support workflow management (Bussler and Jablonski 1994, Du et al. 1995, Schlatter et al. 1994), and conventional transactional models are being modified to encompass the complex coordination requirements of workflow applications (Hsu 1995, Rusinkiewicz and Sheth 1993).

An organization is typically involved in three types of activities (Medina-Mora et al., 1992): material processes, information processes, and business processes. Material processes refers to the activities required to transform physical components into products. Information processes use sophisticated information technologies to manage the flow of information to perform various activities such as data flow analysis, database storage and retrieval, transaction processing, and network communication. Business processes embed the interactions between customers and suppliers with the organization in order to achieve business goals. Workflow management is mainly involved with managing the information needs and transitions in business processes.

Van Der Aalst, (2000) described three dimensions of workflow management: control-flow, resource, and case dimension (Figure 1). The control-flow dimension is concerned with the partial ordering of tasks, i.e., the workflow process. The tasks which need to be executed are identified and the routing of cases along these tasks is determined. Conditional, sequential, parallel and iterative routing are typical structures specified in the control-flow dimension. Tasks are executed by resources. Resources are human (e.g., employee) and/or non-human (e.g., device, software, hardware). In the resource dimension these resources are classified by identifying roles (resource classes based on functional characteristics) and organizational units (groups, teams or departments). Both the control-flow dimension and the resource dimension are common across all cases. The third dimension of a workflow is concerned with individual cases which are executed according to the process definition (first dimension) by the proper resources (second dimension).

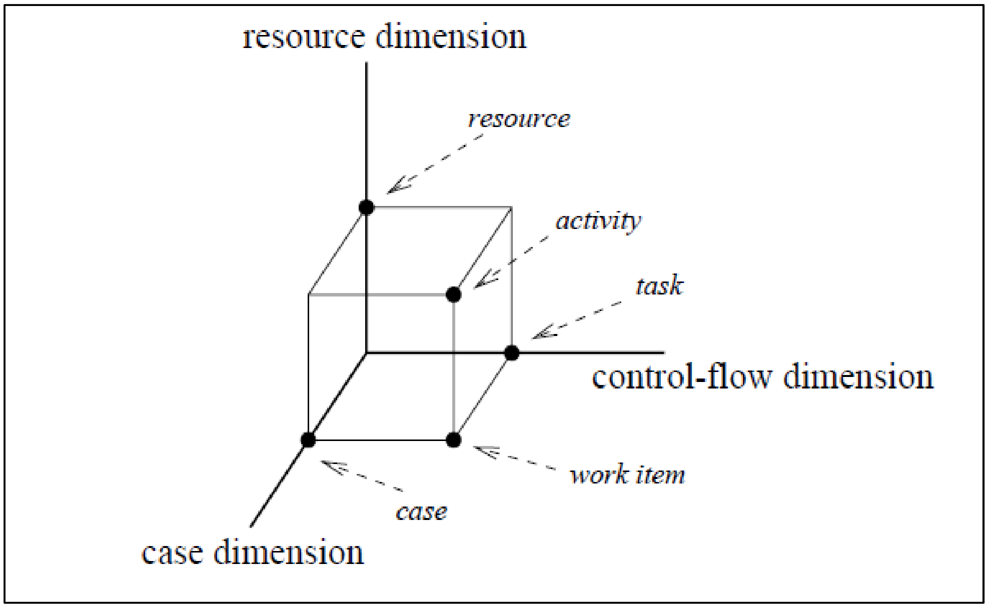


Figure 1. The Three Dimension of Workflow

In a healthcare system, the control-flow dimension represents the workflow process and tasks of the care providers along the continuum of care. The resource dimension represents the information that is required to provide appropriate services for patients. The case dimension represents individual patients. In a well-coordinated health system, the care providers need to be accurately informed about the patients that they visit at any point of time along the continuum of care. The accuracy and pace of transition of information from one point of care to another affects the activities and interventions that the care providers implement for each individual patient. By analyzing the information available through health information systems as well as the information needs of the activities and roles responsible to complete these activities, we can identify sources of error and opportunities for improvements. I investigate the workflow in continuum of care for patients with heart failure to identify impactful interventions that can help to improve the quality of care delivered while reducing costs.

2.4. Self-Determination Theory

Self-determination theory (SDT) is a macro theory of human motivation and personality. SDT focuses on the level of self-motivation and self-determination in individuals' behavior to achieve their goals and satisfy their needs (Deci and Ryan, 2012). SDT draws a distinction between intrinsic motivation and extrinsic motivation. Intrinsic motivation refers to individual's inherent incentives to engage in a behavior mainly as a challenge or enjoyment. However extrinsic motivation involves doing an activity in order to achieve a specific and pre-identified goal. SDT proposes a continuum for the internalization of motivation, whereby individuals become more self-determined to engage in behaviors over time as their extrinsic motives or reasons become more internalized. Facilitation of this internalization process has been found to nurture more autonomous motivation with an ensuing predictive influence on adaptive outcomes such as behavioral engagement/persistence and well-being (Ryan and Deci, 2002; 2008). According to SDT, it is those social environments that support individuals' basic psychological needs specifically (i.e., autonomy, relatedness, and competence) that are assumed to foster more autonomous motivational patterns as well as adaptive outcomes.

SDT has received significant empirical support in the context of health behavior change (Fortier, Williams, Sweet, Patrick, 2009). One of the strengths of SDT is that it offers malleable processes of behavioral change that can be targeted in different health behavior interventions (Fortier, Sweet, O'Sullivan, Williams, 2007). The literature suggests that SDT can be used to develop instruments that assess and inform accurate self-care behaviors for patients. These behaviors can potentially impact the costs and quality of care that a patient with heart failure receives. I study the development and impact of such interventions in this dissertation.

2.5. The Chronic Care Model (CCM)

The Chronic Care Model (CCM), developed by Ed Wagner and colleagues, emphasizes high-quality care for chronic disease. It also was developed to provide a performance improvement framework for hospitals and patient care (Wagner, Austin, Davis, Hindmarsh, Schaefer and Bonomi, 2001). There are six elements to the CCM, community, health system, self-management support, delivery system design, decision-support and clinical information systems (Coleman, Austin, Brach, and Wagner, 2009). CCM helps to develop an active relationship between patients who are informed and their healthcare team. In addition to these six elements, five additional themes were added into the Expanded CCM, which are patient safety, cultural competency, care coordination, community policies and case management (Barr et al., 2003, p.77). The Expanded CCM included community, the health system and population health to provide a comprehensive overview of chronic disease care. The Expanded CCM adds a special focus on information systems including building new programs, evaluating established ones and supporting new ways to provide care (Barr et al., 2003). Expanded CCM attempts to address individual health, population health and clinical outcomes (Barr et al., 2003). The goal of CCM is to make patient's daily care of chronic conditions proactive, planned and population-based instead of acute and reactive.

The CCM, as well as the expanded CCM, provides a framework to study patients along the continuum of care. Chronic conditions require proactive action on the part of the healthcare providers, the healthcare system as well as on the part of patients with chronic conditions. By situating research in the CCM framework, we are able to build a holistic understanding of the care of chronic heart failure patients. In this dissertation, I adapt and build from the chronic care model to study impactful interventions for heart failure patients.

These theories provide a common foundation from which I build my three essays presented in this dissertation. In the following chapter, I will discuss each essay in more detail and provide the research design and timeline for their completion.

CHAPTER III

ESSAY 1_ HEALTHCARE SYSTEM COORDINATION NETWORK

3.1. Introduction

Managing costs while improving quality of the service delivered is a perennial research challenge in business and in information systems. Recently, much research attention is focused on the application of information systems to healthcare to improve efficacies while providing improved quality of care. Specifically, there is focus on use of technology and Information Systems techniques that can improve the set of clinically feasible and administratively viable alternatives that are available to both clinical and administrative decision makers to reduce systemic costs and improve the quality of services provided.

In 2012, the Centers for Medicare and Medicaid Services (CMS) implemented the hospital readmissions reduction program in which payments would be reduced for hospitals with “excessive” readmissions in 30-days as judged against a benchmark for common but significant conditions including heart attack, heart failure or chronic obstructive pulmonary disease (COPD). Section 3025 of the Affordable Care Act, which established the hospital readmissions reduction program, requires that CMS reduce payments to hospitals with excess readmissions, effective for discharges beginning on October 1, 2012.

Similar programs, such as the hospital acquired condition reduction program, under the inpatient prospective payment system (IPPS) regulations and notices provide for significant financial incentives and penalties.

These are a significant driver for hospitals and healthcare systems to manage costs, improve quality and provide better care simultaneously. This is the complex challenge for today's healthcare system - to meet continually increasing standards of quality of care delivered while meeting increasingly exacting cost standards.

Technology is an important variable in understanding the actions of complex organizations. Thompson (1967) identifies three varieties of technology that are widespread and sufficiently different – long-linked, mediating and intensive technologies. Long-linked technology involve serial interactions between activities for effective coordination. These are further expanded by Malone and Crowston (1994) as flow, fit and sharing coordination mechanisms. Mediating technologies develop and impose a level of standardization in the communication and coordination of interactions and activities among various actors in order to achieve the objectives of the organization. Thompson identifies *Intensive Technologies where a variety of techniques may be employed in order to achieve an objective, yet the specific selection, combination and order of application are determined at the site of application based on feedback from the object where they are applied.*

Interestingly, to illustrate intensive technologies, Thompson uses the example of a hospital where each patient may require a specific combination of therapeutic, clinical, administrative activities and processes in order to develop the unique care plan for the patient. He notes that intensive technologies are custom technologies that are require availability of all capabilities and capacities needed, that are then purposefully combined to meet the objective of the current case. He notes that the intensive technology is “most dramatically” illustrated in the healthcare context where the selection, combination and order of application are determined by the adjustments needed for the effective care of individual patients’ conditions. In other words, each case is unique and the care coordination for the case has to be adjusted accordingly. This represents the most challenging form of coordination. Effective accomplishment of objectives requires dynamic mutual adjustment of the activities and resources of multiple boundary spanning units needed to provide effective care while managing costs. Given the heterogeneity of patient conditions and their unique care requirements, effective dynamic coordination of activities to deliver effective care is a dynamic and complex task.

For dynamic task environments, where there is some level of similarity in the cases, a differentiated or sub-divided unit or department may be established to monitor the environment. The more dynamic the task environment, the greater the contingencies presented to the organization. The organization must put boundaries around the scope of adaptation needed. This is achieved by structural units specialized to face a limited range of contingencies within a limited set of constraints. In healthcare organizations, transitional care clinics are such boundary spanning organizations that are employed to manage the complex coordination needs for patients across multiple care providers.

Transitional care programs are actions designed to coordinate the continuity of healthcare as patients transfer from one care facility to another within a health system or to home environment (Albert, 2015). Naylor, Aiken, Kurtzman, Olds and Hirschman (2011) identify that points of transition of patients and their information, contribute to high healthcare costs, and low quality of care due to increased potential for errors or delays in the timely coordination of information. Mechanisms to manage patient flow and transition care programs are complementary interventions. Management of healthcare organizations can use these interventions to systematically administer improved patient flow over the complete care continuum. Stamp, Machado and Allen (2014) provide an integrative review of the clinical and operational impact of transitional care programs on patients with heart failure (HF).

The American Heart Association scientific statement in 2015 (Albert et al, 2015) calls for impactful research to identify best practices for economically effective and clinically feasible transitional care programs. This essay addresses the research question: *How can we identify effective components of transitional care programs that are both feasible to implement and provide cost effective care for heart failure patients?*

We present methodology to identify those impactful interventions that are both administratively feasible and clinically viable. We utilize Thompson's theory of intensive technology as guiding theory for our analysis and interpretation. We illustrate the application of our methodology in generating insights that can be implemented in a clinical setting to provide effective transitional care. Our research offers new insights on analysis of the processes and mechanisms that can be employed in intensive technology situations, which are characterized by high levels of heterogeneity in a dynamic task environment.

Most current studies in healthcare are quantitatively driven. The attempt to apply advanced statistical and analytical techniques to improve predictive ability of analytics. They identify more refined sets of variables and offer advanced methods to explain and predict patient readmissions, or other measures of the quality and cost of care. Most of these approaches take an "outside-in" view in that they provide an *etic* account of the care process and attempt to predict future instances. The complementary yet equally useful "inside-out" or *emic* analysis of the care processes that result in potential errors often critically missing. We illustrate how an emic analysis allows for the deep and contextualized examination and identification of the common issues. This leads to richer explanations of the nature and reasons for issues that can inform clinicians, healthcare administrators and decision makers as they identify and analyze impactful interventions to improve quality and costs of care. Moreover, analysis to identify opportunities for improvement in the workflows related to the care process provides systems designer a methodology for contextualized identification of design improvements that can reduce errors and their related unnecessary costs, improve care coordination within and across the organization and lead to improved quality of care.

In this paper, we present a detailed case study to illustrate our development and application of an analytical framework to identify root causes of coordination problems in the care of heart failure patients. We explain how qualitative data about the patient flow can be systematically analyzed to develop clinical, administrative and design guidance to improve the care of heart failure patients in a large (~1000 bed) regional hospital system. Analysis of rich and in-depth qualitative data in the form of multiple interviews, documents and meeting notes allows us to consider the various perspectives of clinicians, administrators, systems and analytics personnel. We explain how our analysis develops recommendations that are contextually relevant as well as clinically feasible and administratively viable. We discuss the implications for systems design to capture inefficacies and improve the flow of patients in the care continuum. We apply our analytic techniques to the critically relevant issue of the patient flows involved in the care of heart failure patients. We discuss the opportunities for improvements in the systems that coordinate care and manage the flow of information across the continuum of care for patients with heart failure.

The remainder of this essay provides a review of literature about coordination of care and patient flow in an intensive technology environment and provides the insights from our case study of a local health system.

3.2. Coordinating Care in Intensive Technology Environment

In healthcare, the specific and unique sequence of activities needed for the coordinated management of activities to achieve clinical objectives for each specific case is contingent upon feedback from that case. In Intensive technology environments

(Thompson, 1967), the selection, combination, and coordination of technical and clinical activities are determined based on the nature and characteristics of the individual patient. This is particularly applicable in healthcare processes, where each specific case requires its own specific and unique care plan, with the unique set of activities and resources necessary for effective treatment. Often, these resources and capabilities may need to be garnered from different parts of the organization or from affiliated care providers. According to Joint Commission (Litvak, 2010), understanding specific mechanisms to implement management structures and techniques that can handle such dynamic and varied situations remains an open research question.

The environment is a dynamic environment where coordination structures are effectively developed using a combination of coordination by standardization of procedure, coordination by plan as well as coordination by mutual adjustment in order to manage the uncertainties that healthcare operations present. Coordination by mutual adjustment may involve communication across hierarchical lines where the units are reciprocally interdependent, where the inputs for one unit may come from the output for the other. The more variable and unpredictable situation, the organization has a greater need to rely on coordination by mutual adjustment or coordination by feedback (Grant, 1996). In healthcare systems, multiple specialties and functional units are mutually and reciprocally dependent on one another to provide cost-effective and high-quality care for patients. HF and other chronic conditions are particularly characterized by the prevalence of co-morbidities. Chronic Heart Failure (CHF) patients often suffer from multiple chronic conditions that frequently occur together. A specific patient may need to be referred to another specialty unit for tests or therapies and/or clinical procedures and the care needed from the referring unit may depend significantly on feedback from the unit that the patient was referred to. Coordinating such care requires the effective flow of information between the units providing the care. This includes dependencies and contingencies that arise from administrative systems, such as scheduling of appointments and follow-ups, as well as those that arise from clinical systems, for example results of tests and medication adjustments.

Thompson (1967) notes that in such situations, it is in the interest of the organization to create boundary spanning units to monitor the environment and manage coordination challenges. If the task environment is dynamic in clusters of heterogeneous patients, the boundary spanning component needs to be primarily concerned with the development of dynamic responses to manage the necessary contingencies and reciprocal interdependencies for each case, in order to provide high-quality clinical care in a cost-effective manner. Transitional care represents such a boundary spanning mechanism that seeks to coordinate effective care of each patient based on their unique needs and constraints. In this view, the transitional care clinic (TCC) becomes the mechanism to manage uncertainty and implement a contingency-based approach to provide effective quality of care while simultaneously managing costs. While the clinical literature recognizes the potential of transitional care programs, methods to identify the nature of clinical and administrative activities needed for effective transitional care in a given healthcare setting remain elusive.

Our analysis reveals methodology to identify the tasks that the TCC would do in order to meet the dynamic coordination challenges that are needed in highly dynamic task-environments that characterize intensive technology environments.

3.3. Understanding Patient Flow in the Continuum of Care

Patients are admitted, discharged or transferred from one care facility to another on a daily basis within and across hospitals, clinics and other service providers. Hospitals seek to optimize patient flow to provide efficient and effective medical services at lower cost. Inefficient patient flows create challenges including time and resource allocation constraints for both clinical care providers and hospital management teams (Litvak, 2010). Crowded emergency rooms, long stays in hospital and high readmission rates manifest inefficient patient flow (Peacock, Beaunwald and Abraham, 2010). Patient flow management is strongly associated with the overall quality and cost of healthcare (Pitts et al. 2008, Niska et al. 2010). The joint commission resources (http://www.jcrinc.com/) note the "far-reaching" impacts of patient flow on patient care as well as the multiple aspects of hospitals' operations, quality, patient safety and potential revenues.

Hospital readmissions of patient with heart failure has been one of the main contributors to inefficient patient flow. Readmissions are generally indicative of poor quality of service and unnecessary costs associated with health service providers. They are often associated with errors and shortcomings such as incomplete discharge orders and inadequate verbal and written communication between patients and their care providers to guide and inform patient needs (Messina, 2016). The main drivers of high cost of care for patients with heart failure (HF) are frequent hospital admissions and unnecessary readmissions (Voigt and Mosier, 2012). Patients with HF have a higher readmission rate (20%-25%) within the first month of discharge than any other common medical condition (Voigt and Mosier, 2012).

Cost of care for HF patients exceeds $12 billion per year (CMS, 2012). To reduce this cost and decrease the frequency of re-hospitalization, The Accountable Care Act authorized The Readmission Reduction Program in 2012. This program enforces reduction in the reimbursements for hospitals with excessive risk-standardized 30-day readmission rates. Therefore, identification and implementation of impactful interventions to avoid readmission is critically important for heart failure care providers.

Current research has focused on ways to understand and address this problem. Jack and Powers (2004) developed a research framework to study the highly dynamic and uncertain demand characteristics that health services face and investigate volume flexibility as a strategy for healthcare organizations to improve the services they deliver in a manner that uses their scarce resources in an effective manner. They identify mechanisms to develop volume flexibility in their resources in manner that allows them to leverage these resources to meet random and uncontrolled demand for health services. Salzarulo, Bretthauer, Cote and Schultz (2011) study how high levels of variability in demand for health services, evident from ad-hoc patient arrivals, impacts the pressures on health care providers. They identify systematic inflows of patients and the consequent ability to schedule resource allocation, as well as on-demand availability of patient information, as influential factors in improving service quality and managing costs. Venkat, Kekre, Hegde, Shang and Campbell (2015) analyze adult emergency room visits to explain strategic management of health care operations and study the financial workflows of the emergency department. They identify the need reengineer operations in a manner that makes appropriate strategic consideration of the allocation of resources and controlling costs, while improving the impact on population health and patient satisfaction. Helm et al., (2011) study the hospital admission control process and its impact on the operational effectiveness of the hospital. They delineate the two primary mechanisms for patient inflow, emergency department and scheduled visits, and find that high queue times for scheduled visits create incentives for patients to utilize emergency departments as a surrogate, yet undesirable, mechanism to manage their wait times. This creates undesirable operational burdens for the system and becomes a source of avoidable costs for patients, the hospital and insurance providers or Medicare/ Medicaid. They propose a policy intervention, an expedited patient care queue, as a mechanism to balance the priority of patients in the admission queue. Interestingly, Devaraj, Owand Kohli (2013) find that quality and cost of care are not conflicting objectives. They demonstrate that effective management of patient flow positively impacts both the clinical and managerial objectives of the quality and cost of care.

Review of these and many other related studies, we see a convergence of ideas that call for teleological analysis of the process to develop and study the impact of innovative management interventions to reduce or manage demand uncertainty, improve the efficiency and effectiveness of resource allocations and resource utilization, while at the same time meet the challenge of providing improved quality of care for patients to meet the demands of external regulatory and insurance agencies. Identification of the potential systematic data flow errors or control flow errors help health systems to improve their resource allocation and manage utilization of resources in a health system.

3.4. Transitional Care Programs and Care Coordination

Heart failure (HF) is a chronic condition. It is not completely curable. A patient's HF diagnosis remains in their clinical diagnoses irrespective of whether the primary reason for admission, the primary diagnosis, was HF or any another condition. HF patients need to manage their symptoms for the rest of their life. Multiple co-morbidities are often clinically associated with HF. For example, a patient may be admitted for renal failure, but should still be seen by their cardiologist, to assess the impact of the renal care on their HF. This makes care coordination particularly challenging. The clinical literature identifies transitional care programs as a complementary approach to potentially improve the quality of care for patients.

Complexity in the care needs of HF patients lends itself to a greater potential for information errors. This can have significant impact on the cost and quality of care, not to mention patient lives. Moreover, the care environment characteristics, including systems integration and operation management may present challenges to providing cost-effective quality care in a well-coordinated manner. Multiple services including emergency, cardio-vascular, and other specialized care facilities such as renal and pulmonary clinics must often coordinate activities to provide effective HF care. Moreover, associated professional care clinics and primary care physicians (PCP) offices coordinate care for HF patients in the health system. These, more independently managed facilities may have varying levels of technological integration of electronic medical record (EMR) and other clinical and administrative systems. These contribute to the complex and critical nature of coordination and communication needs among the multiple care providers in order to care for HF patients effectively.

The Agency for Healthcare Research and Quality (AHRQ) acknowledged that poor coordination of care, discontinuity between care providers and poor transitions from hospital to home, are the main contributors to HF patients' readmission. Several studies (eg. Peacock et. al., 2010) suggest that a heart failure observation unit that provides personalized disease management will help to streamline the flow of patients with heart failure. They claim that this approach improves short-term outcome and reduces inpatient length of stay. These personalized disease management units might be in the form of heart failure camp or day treatment centers or it could be incorporated into inpatient post-discharge care or transition clinics. They call for more research to define the management techniques that help to improve quality and cost of care using this strategy.

Figure 2 shows the current patient flow of heart failure patients along the continuum of care and emphasizes on the highly unscheduled and ad-hoc Emergency Room (ER) visits. Implementation of transitional care clinic as an intervention at the point of discharge, systematize the demand flow by shifting patients to a scheduled pattern of arrival. We investigate these interventions that can be implemented in the transitional care clinic at the point of discharge to streamline the flow of patients in the hospital and avoid unpredictable hospital visits.

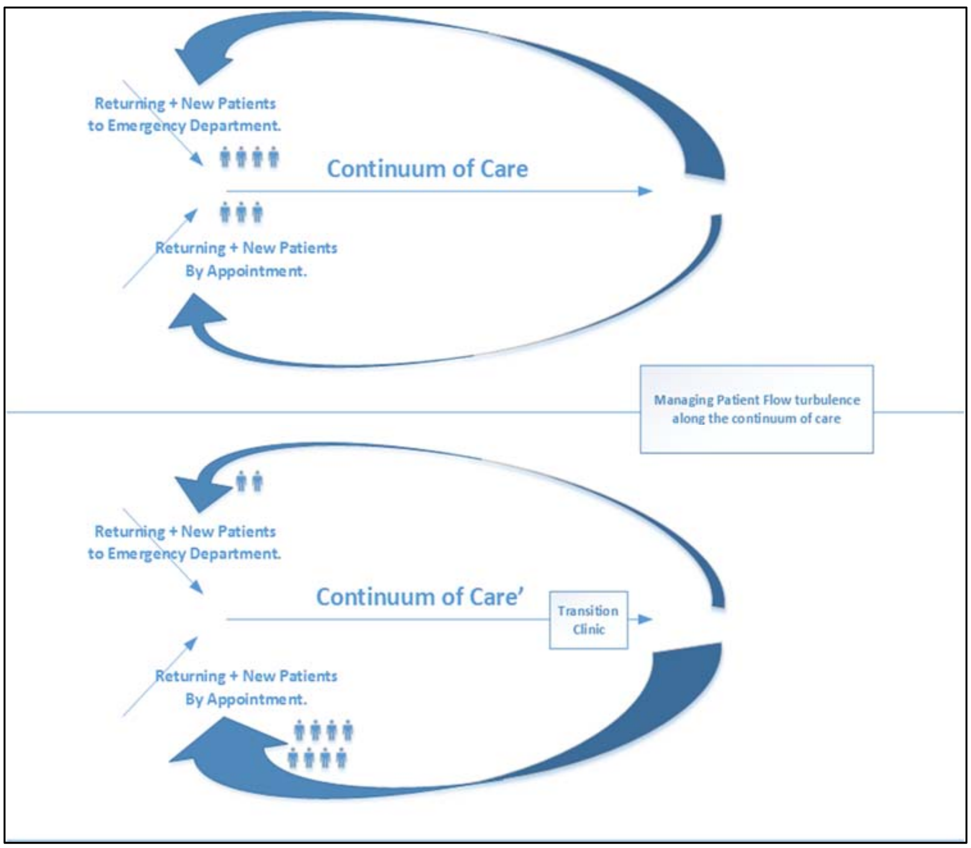


Figure 2. Managing the Turbulence in Patient Flow along the Continuum of Care through Transitional Care Clinic.

3.5. Research Context and Design

The context of this research is the effective care of patients with congestive heart failure (CHF). We employ case research methods to investigate the clinical and administrative workflow in a single hospital for heart failure patient and identify the control-flow and information-flow errors. The purpose is the identification of potential systematic control-flow and information-flow errors in order to inform care providers' strategies and interventions to improve their allocation and utilization of resources. We take an in-depth multi-method (Mingers, 2001; 2003) investigation into the impact of transitional care on the quality and cost of care for heart failure patients. For our research, multi-method refers to the use of multiple methodologies in a single qualitative analysis paradigm to draw insights and proffer direction on the nature of interventions that may be suitable for transition care clinics at a facility.

Literature identified that points of information transition are critically important. These are often the most error-prone and vulnerable to information loss and inaccuracy (Naylor et al., 2011). Transition of accurate and workable information at the right time to the right actor performing the right activity can improve the quality of care for patients along the continuum of care. Our work offers insights on how to analyze the essential components of information based interventions and analyze their impact on the coordination of information required to effectively identify and implement impactful interventions.

We apply multiple data collection techniques including semi-structured interviews, observations, gathering documents detailing planning and procedures as evidence to derive and interpret multiple perspectives on the phenomenon. As stated earlier, our purpose is to develop analytical insight into transitional care clinics as effective clinical and administrative interventions that improve the quality and cost of care available for heart failure patients. We apply case-study and qualitative approaches to identify the nature and characteristics of information and resources from the multiple *touch points* where both clinical and administrative staff interact with patients.

A case study employs multiple methods of data collection to gather information from one or a few entities, to examine a phenomenon in its natural setting (Benbasat et al., 1987). This research approach is appropriate for studies where a priori knowledge of the variables of interest and their measurement is lacking. First, a convergent set of concepts that are common across the various care facilities must be identified and validated to describe the information and coordination components for effective transitional care. Further investigation and analysis leads to understanding the control and information errors along the continuum of care for HF patients and investigate impactful interventions that help to improve the quality of care while maintaining costs. We use coordination theories (Thompson, 1967; Malone and Crowston; 1994; and van der Aalst, 2000, 2005) to develop an investigation framework that identifies information and control errors along the continuum of care. We demonstrate how this framework can be applied to identify appropriate interventions and inform decisions to implement appropriate interventions that are viable and feasible to implement in healthcare systems.

3.6. Case Organization and Data

We study transitional care clinics (TCC) at a large not-for-profit network of health care providers serving multiple communities and counties in the eastern US, with over 10,000 employees and 1000 physicians. We focus our attention on the Heart and Vascular Center (HVC) that houses the Advanced Heart Failure Clinic (AHFC) to care for advanced heart failure patients. This focuses will help us to understand the challenges and concerns along the continuum of care from the clinical workflow stand point. We also include clinical and administrative perspectives of the accountable care organization (ACO) in this hospital system to capture the managerial and administrative issues along the continuum of care for patients with heart failure.

To build an accurate understanding of their needs, we triangulated multiple data gathering sessions including field studies, interviews, and observations of clinical and administrative staff and shadowing of care providers as they treated HF patients. Over the last year, we conducted 25 interviews with multiple key staff in both clinical and administrative departments and analyzed transcripts and, examined minutes of multiple by weekly internal meetings between ACO and clinical staff. Specifically, we conducted multiple interviews with the Head of Advanced Heart Failure Clinic, Nurse Practitioners and Physician Assistants, Head of Pharmacists, Nurse Director of heart failure unit, as well as Executive Director of Healthcare Analytics, Quality Managers and EMR administration and training units. We also interviewed and ride with Community Paramedic who provide home care for selected patients with heart failure. Table 1 shows our sources and observations for data collection.

Table 1. Sources of Qualitative Data Collection

Source	**# of interviewees**
Cardiologists and Heart Surgeons	4
ED Specialists	2
Pharmacists	2
Nurse Practitioners and Physician Assistants	4
Nurse Director (CHF Unit)	1
Nurses	5
Community Paramedic	1
Quality Manager (ACO Unit)	3
Information Analytics and EMR Administration	3

We started sampling for interviews based on guidance from senior management and we used the snowball approach to identify additional interviewees. Participants ranged from senior management to the care providers who interact with patients every day. Interviewing individuals at multiple layers from clinical and administrative units allowed us to capture the full perspective of continuum of care for patients with heart failure and understand both clinical and administrative workflows. Each interview followed an open ended protocol with respect to the position of the interviewees and their level of interactions with patients. Questions were about their perspective of challenges pertaining patients with heart failure and their perspective of transitional care clinic as an intervention and its impact on care coordination and quality of care.

In addition to the interviews, we observed and shadowed two nurse practitioners and one cardiologist to understand their workflow and their interactions with patients. We attended several by-weekly care management meetings that aimed to identify ways that can enhance the quality of care for patients with heart failure in the hospital. In each case our purpose was to identify and analyze patient workflows and study the impact of introducing the transitional care clinic on the patient flow, the clinical workflow and the administrative workflow.

Table 2. Data, Approach and Expected Outcomes

Data	Approach	Expected Outcome
Semi-structured Interviews	Recursive abstraction, Text Mining	Convergent set of concepts related to HF Quality of Care and Cost of Care influencers.
Quality Management and Improvement Documents	Content Analysis	Analysis of continuum of care workflow of HF Patients.
Activities, actors, roles and information from HF continuum of care	Workflow Analysis identifies errors and possible interventions	Items and Functional Requirements, Potential Causes of Failure

3.7. Data Analysis and Outcomes

In this section we explain our multi-method approach using text mining as well as workflow analysis and present the results.

3.7.1. Text Mining

We applied text mining techniques using SAS enterprise miner to identify the critical concepts and links that comprise the ontology of transition of care in heart failure across the range of data sources. Text mining is a knowledge extraction technique that allows us to identify and extract concepts and relationships in large volumes of data that may lead to discovery of new concepts or verification of existing relationships. Cohen and Hersh (2004) provide an interesting survey of the current state of the art in biomedical text mining. They speak to the utility of the techniques and call for more work to identify better methods that will help researchers to better understand the context, identify concepts and measure the strength of relationships.

We transcribed the interviews, minutes of the meetings and observation notes and used text mining techniques to unearth the primary and most prevalent concepts of transitional care clinic and its impact on quality and coordination and the relationships between those concepts.

We used SAS text miner to perform descriptive mining and discover the prevalent themes and concepts in the data. We decomposed textual data and generated quantitative representations of each concept that help to identify the association between the central concepts in an informative format. We generated conceptual maps from our textual data to illustrate the strength of the relationships between the concepts of interest. These conceptual maps allow us to investigate the themes and concepts in the qualitative data and provide detailed information about the terms, phrases, and other entities in the textual collection.

3.7.1.1. Readmission

Results of text mining analysis shows that the concept of *Readmission* is highly associated with cost for hospitals. It is also associated with high risk patients and emergency room visits. The conceptual map is presented in figure 3.

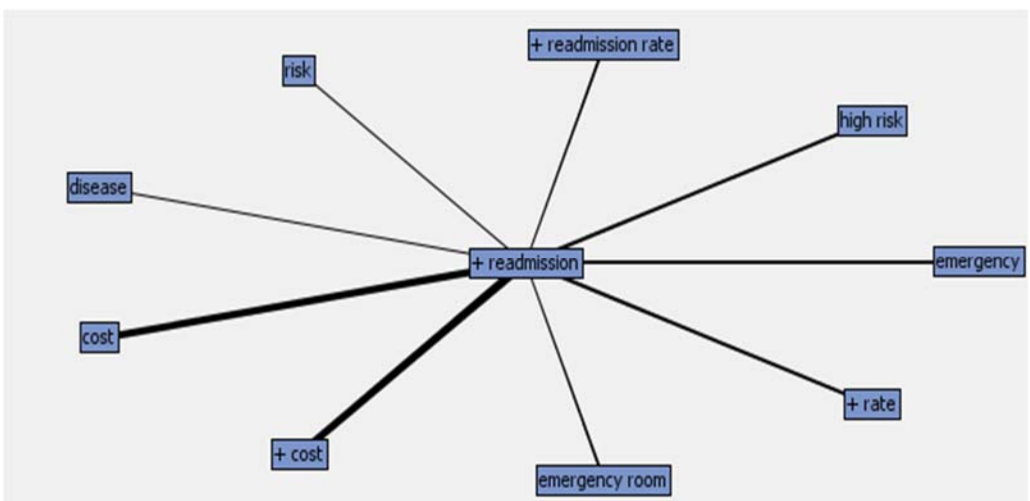


Figure 3. Conceptual Map of Readmission for HF Patients

3.7.1.2. Costs

Next, we decomposed the concept of *Cost* and identified that it is highly associated with Emergency room visits, preventive care and home care. Patients' frequent visits to emergency rooms are costly for hospitals and lead to inefficient patient flow. Our conceptual mapping validates and emphasizes this finding and suggests that providing preventive care interventions as well as home care will help to reduce the costs of care for patients with heart failure. The conceptual mapping is presented in figure 4.

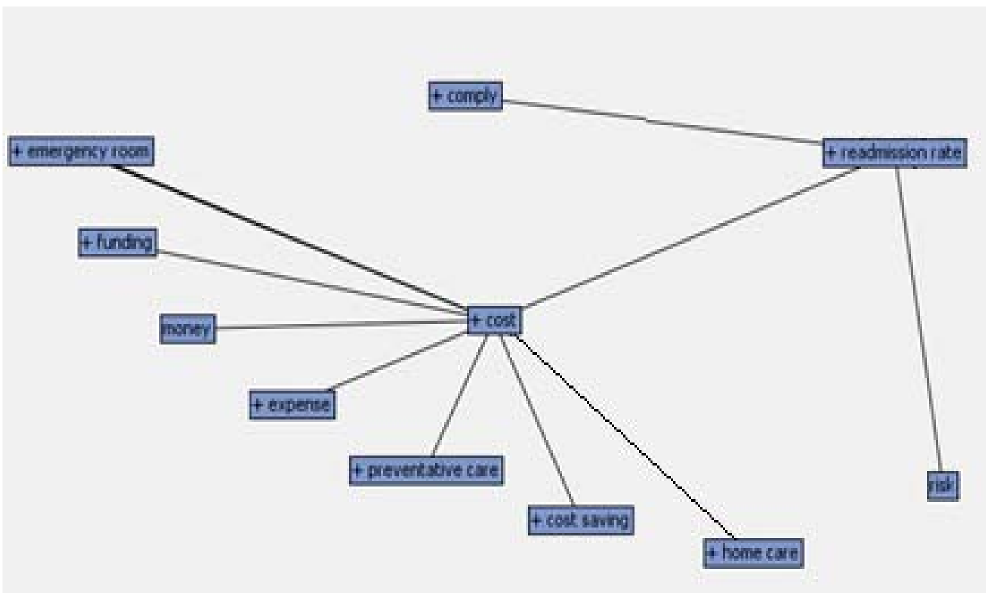


Figure 4. Conceptual Mapping of Cost of Care for HF Patients

3.7.1.3. Transitional Care Clinic

We concentrated on the concept of transitional care clinic (TCC) and identified that it is highly associated with patient care and system. The care system is associated with healthcare providers such as primary care physicians and nurses and coordination of care between various medical centers. TCC is also associated with patients understanding of their medication and health condition. The conceptual mapping of the TCC concept in presented in figure 5.

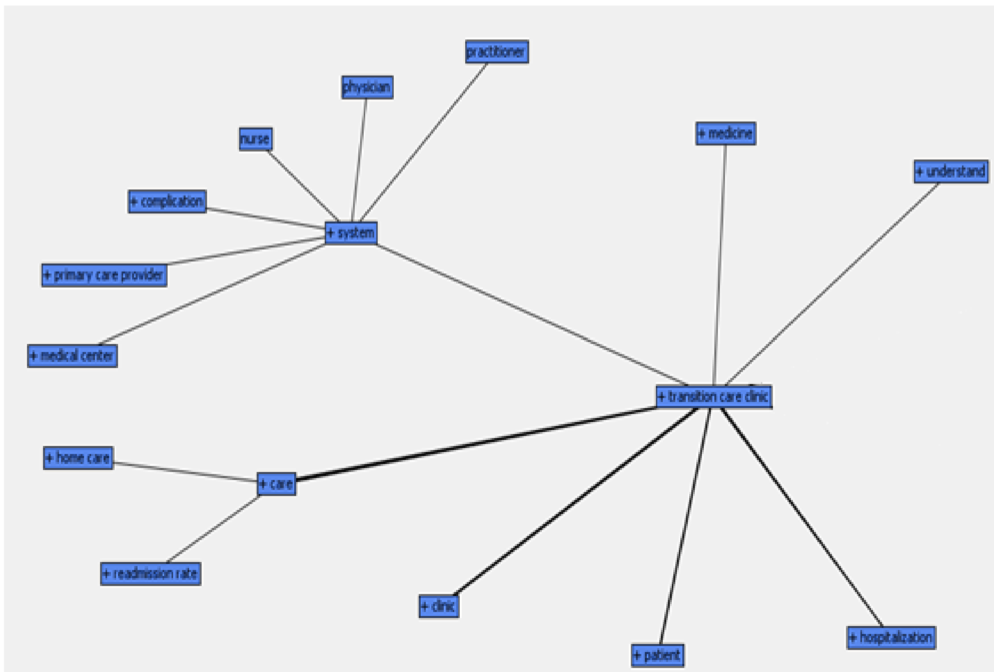


Figure 5. Conceptual Mapping of Heart Failure Transitional Care Concepts and Links

Our text mining approach shows that transitional care clinic is highly conceptualized as an intervention that helps to reduce cost of care and reduce readmission rates and ER visits for patients with heart failure. This intervention is a mean to coordinate multiple care facilities and educate patients about their health conditions and medications. For example, multiple care facilities may mutually adjust their schedules and materials to coordinate the care of a patient and engage in patient education about medications as well as self-care management processes that are coordinated so that there are no negative interactions. The more variable and unpredictable the situation, the organization has a greater need to rely on coordination by such mutual adjustment or by feedback.

3.7.2. Workflow Analysis

In the healthcare workflow of a patient, commonly called the patient flow, the transmission of accurate and timely information from one care activity to another is critically important in delivering effective care. The coordination network of activities between care-providers are supported by health information systems. All care providers along the continuum of care need access to accurate information about the patients that they visit, at the point of time they are interacting with the patient. They also need to convey accurate information about the patient’s health condition to the next care provider. Naylor, Aiken, Kurtzman, Olds and Hirschman (2011) identify that errors in these transitions of care points contribute to high healthcare costs and low quality of care and are often associated with increased rates of readmission. This often occurs because of lack of proper and cohesive communication between care providers and leads to misunderstanding of medications and health conditions for patients. Patients with lower education about their disease are more prone to medication and diet mistakes that may deteriorate their condition. One objective of transitional care clinics is to implement interventions to reduce preventable readmissions due to patients’ misunderstanding of their medical conditions and smoothing the patients transition form an inpatient setting to outpatient setting.

Our workflow analysis illustrates *how* the dual clinical and managerial objectives can be met while, perhaps most importantly, improving the care process for the patient. Van Der Aalst, (2000) describes control-flow, resource, and case dimensions of workflow analyses. These dimensions provide distinct analytic perspectives to identify errors and opportunities to improve the patient flow in the healthcare system. For example, analysis of the patient transitions from one activity to the next in the care process reveals the challenges and opportunities for improvement in the coordination of tasks. This has implications for the communication of information across tasks, allocation and scheduling of resources for each task as well as the types of coordination necessary for accurate and efficient patient flow. The completeness, accuracy and appropriateness of the information is further identified by the resource dimension, which represents the information that is required to provide appropriate services for patients. These can then be used to analyze individual patient flows and understand challenges and opportunities for improvement in terms of relevant concepts, errors and potential interventions that affect the quality and cost of care for heart failure patients.

Analysis of patients' workflows, including the flow of patients as well as all the administrative and clinical touch points along the patient flow continuum is a critical factor of operational performance, tightly coupled with the overall quality and cost of healthcare (Armony et al. 2015, Pitts et al. 2008, Niska et al. 2010). Analysis of coordination provides a useful context to understand the nature of the activities and their informational and organizational needs (Thompson, 1967; Kumar, Van der Aalst and Verbeek, 2002). Moreover, analysis of the control structures and resource requirements of the activities in a workflow allows us to identify errors in the control of the activities and, importantly, errors in informational requirements (Van der Aalst, 1999).

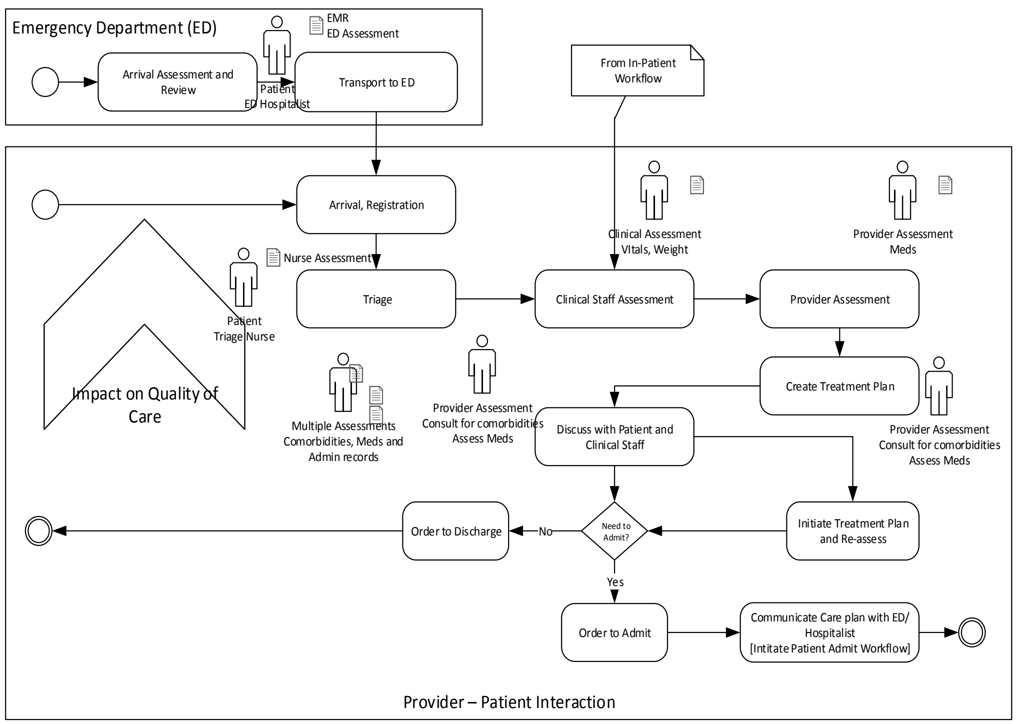


Figure 6. Analysis of Workflow before Transitional Care Clinic

Figure 6 shows the patient and provider interactions in the current patient flow and activities along the continuum of care for patients with heart failure from the time they arrive in the hospital either from ED or by appointment to the point of discharge. We identified different points of care where the patient is assessed and follow the development of the treatment plan for a patient with heart failure. We particularly followed the transition of information from one point of care to another in an attempt to identify the vulnerable points of transition of information as well as the type of information that may get distorted along the continuum of care.

In addition, we looked at the detailed tasks and decisions that are required to be made to transfer a patient with heart failure from ED to Heart Failure Clinic. Figure 7 illustrates these activities. Average waiting time for a heart failure patient to shift from ED to office is about 10 minutes. This may cause their situation to be aggravated. Generally patients are accompanied with an ED staff but sometimes because of the lack of resources the HF nurses have to go to ED and get the patients. These inefficiencies in the egress flow of patients from ED to HFC has impact on the amount of time that HF nurses can spend with each patient and therefore on the quality of care that nurses can provide. The most prominent reason for HF patients returning to ED after discharge from inpatient setting is misinterpretation and misunderstanding of their medications, diet needs and their general health condition. HF nurses require more time to interact with all patients and ensure that they completely understand what they need to do next and understand their medications and encourage patients to ask questions and answer them all.

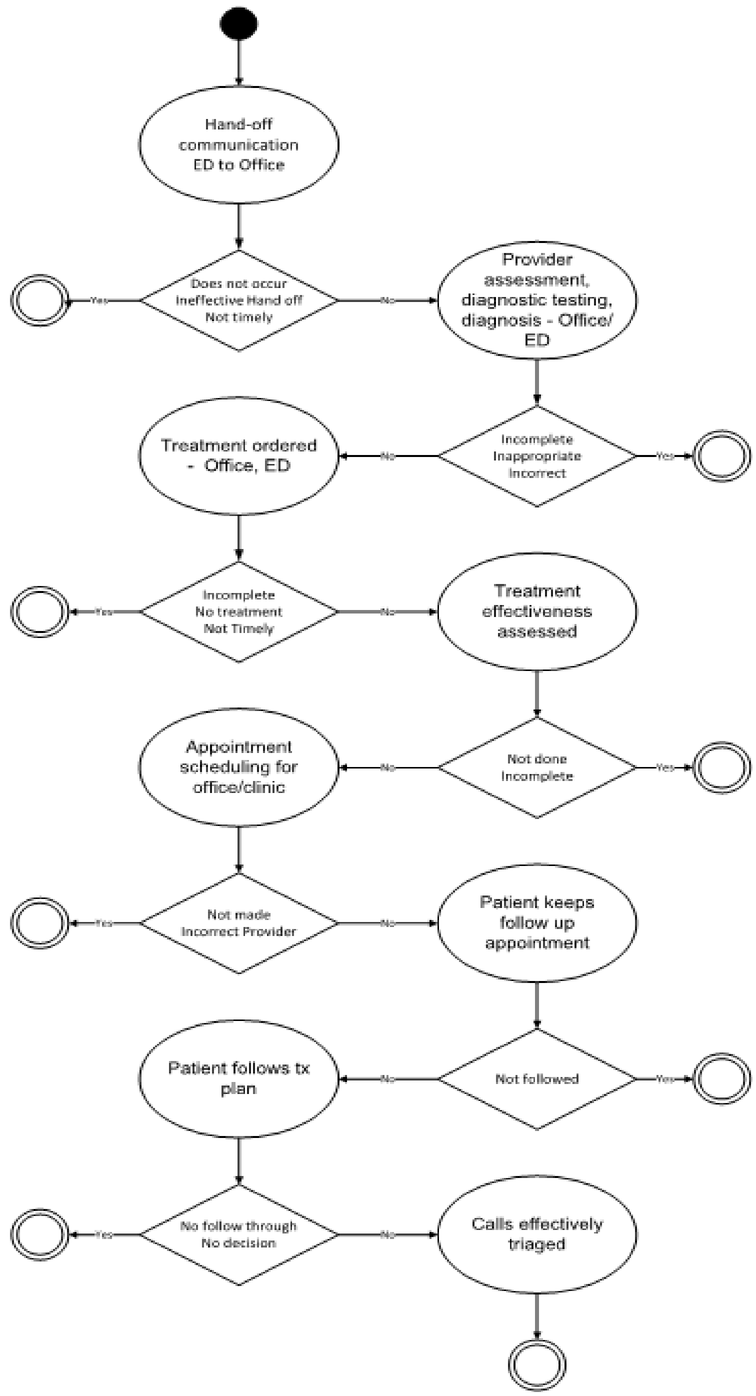


Figure 7. Information Transmission Workflow from ED to Heart Failure Clinic

To identify the interventions that can improve the quality of care for patients with heart failure we investigated the process and resource shortcomings in the inpatient care. This analysis will help us to understand the errors that may lead to extended length of stay for patients in the hospital or potential readmission after discharge. Identification of the causes of readmission and lengthy stays in hospital will inform the strategies and interventions that are need to be designed to improve the quality of care.

Figure 8 shows the cause and effect diagram to investigate the processes and inpatient care as well as resource utilization in hospital and lead to inefficiencies in patient flow in terms of length of stay and readmission.

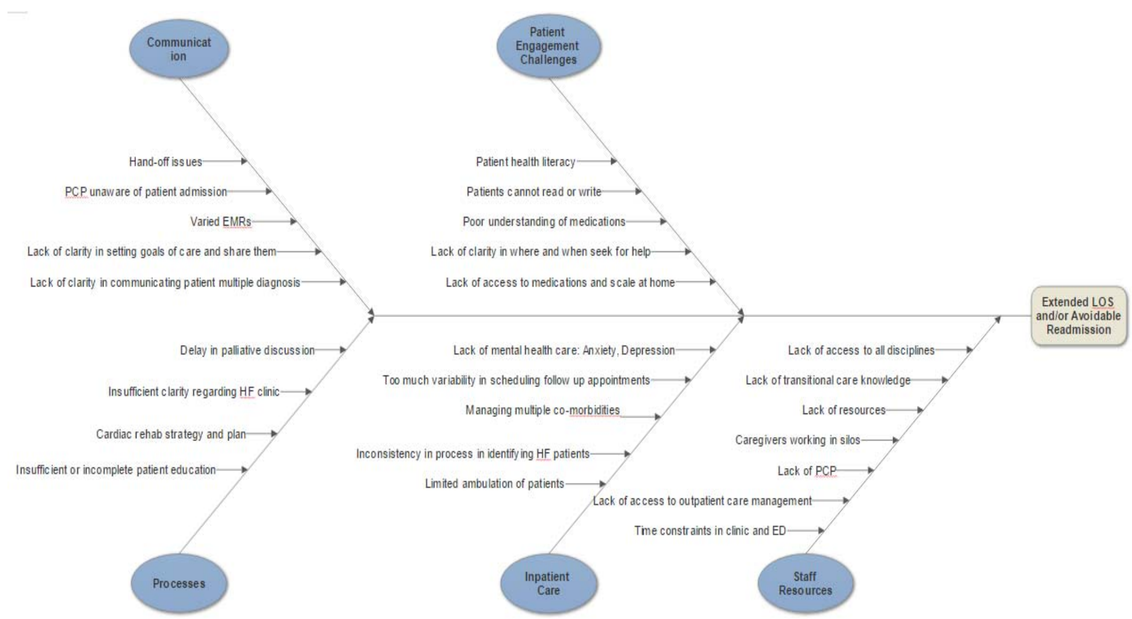


Figure 8. Avoidable Readmission Cause and Effect Diagram

Our analysis identifies activities that are appropriate *triggers* for transitional care. For example, when physicians or clinicians issue orders for medication changes, whether it is for different dosage or change in the actual medication, this triggers transitional care activities including pre-discharge patient education, medication reconciliation, issuance of notification for clinics related to the patients' co-morbidities. For heart failure patients, this is particularly important since often the medication itself does not change, but the dosage is frequently titrated to different levels. Conflicts or inaccuracies in the information has significant implications on patients' health. Vigilance of clinical personnel regarding the issue is noteworthy, yet efforts to improve the accuracy and timely availability of medication information for any care provider in the patient flow is very important. Similarly, each activity along the patient flow requires information from various sources at the right site and at the right time in order for accurate and timely completion. Together these provide the basis for identifying patient workflows as the touchpoints from the managerial and clinical subsystems where actors with various agencies in different roles perform various activities that contribute to the care of the patient. Figure 8 illustrates our findings from workflow analysis and presents various interventions that can be implemented in transitional care clinic at the point of discharge to enhance the quality of care for patients with heart failure.

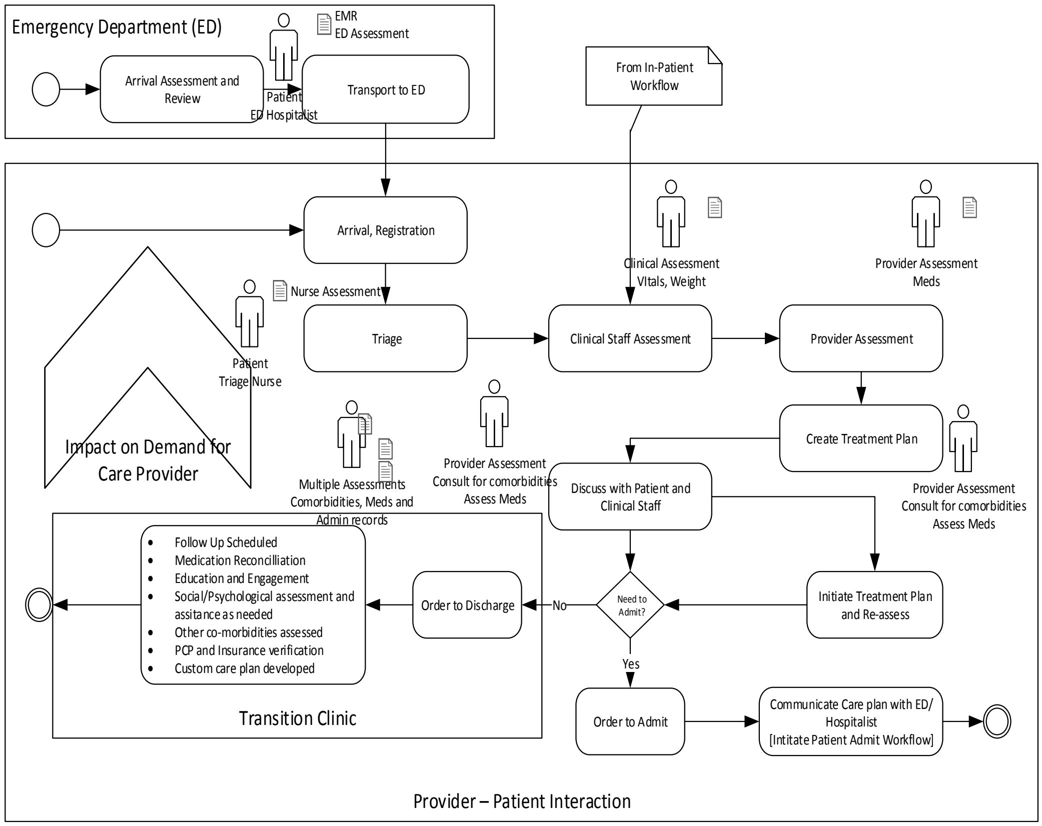


Figure 9. Analysis of Workflows after TCC Implementation

Our analysis identified that one the main objectives of transitional care clinic is to continue the care program with implementing strategies that are enhancing the quality of care for HF patients. Important components of transitional care clinic include ensuring:

- patients have scheduled follow up appointments after discharge from inpatient setting,
- appropriate mechanisms for medication reconciliation, and adjustments after discharge assisted with coordination of care,
- patients engagement in their self-care and their understanding of their symptoms,

- patients education about their health conditions, and preventive measures such as weight monitoring,
- series of follow up appointments either face-to-face or via phone to emphasize and reinforce the medications and required self-care measures,
- integrated system that include assessment and notes of patient's various co-morbidities
- primary care providers' contact information and accessibility for all HF patients

TCC also have to ensure adequate follow up to bridge the patients from the inpatient back to their primary care physician in order to stabilize the inpatient care. We identified that very important parts of this process include making sure that patients have the ability to get their medicines, that they understand which medicines they are on, and they have the ability to follow up appointments.

Each heart failure patient has specific characteristics and needs. Therefore there is high demand for customized and personalized care. Understanding patients' social issues and needs such as their mental health, socio-economic status and their ability to transport to their follow up appointment are some of the examples that needs to be addressed in a transitional care clinic. A full understanding of patient needs, informs the type of therapist and the type of activities that are more efficient for that specific patient. The role of TCC is to established the right care program and stablish right regiment for each patient, and make sure that the proposed treatment actually can be transitioned to patients' homes, considering their specific needs and situation.

In order to provide better transitional care a multicomponent complex set of interventions is required. Transition of care from inpatient to home should be materialized through a focused, comprehensive and multidisciplinary plan that starts from the time of admission and reevaluated as the treatment is provided for the patient that include their health, social, mental and emotional statues. An integrated information system between the nurse and physicians in a transitional care clinic and the primary care provider as well as the social workers and paramedic services would be ideal to serve the needs of customized care for patients with heart failure.

Our proposition is that the initial development of TCC might be costly for the hospital to allocate dedicated human resources and physical facilities. However, a multicomponent set of interventions will help to reduce readmission rates, number of ER visits and number of days in hospital and in this way it reduces the costs in the long run. In essay 2 we empirically test these propositions and investigate the impact of TCC on these quality and cost of care measures.

The traditional model of healthcare reimbursements is based on number of visits and test orders that the provider made. This model is called *"Fee for Service"*. Today, the healthcare industry is moving towards a *"Fee for Value"* environment that calls for systematic improvements in care outcomes while reducing costs across the continuum of collaborative care. The value for funding transitional care clinics will increase, once hospitals implement a more preventive model of *"Fee for Value"*.

3.8. Conclusion

CHF is the most prevalent and costly disease among the elderly, who also exhibit high readmission rates. Heart failure is a chronic disease which is not completely curable. In other words, if a patient is diagnosed with heart failure, they need to manage the chronic condition throughout their life. Moreover, the HF diagnosis is often accompanied by various co-morbidities such as renal failure and chronic lung conditions such as Chronic Obstructive Pulmonary Disease (COPD) (Dharmarajan et al., 2013). Multiple departments including the emergency department (ED), the Heart and Vascular center, as well as multiple specialized care facilities such as renal and pulmonary clinics are involved in providing effective care for patients. Thus, successful care of CHF patients, more often than not, requires effective coordination of care from multiple facilities and specialties within or across healthcare environments. This contributes to the challenging and complex environment of serving the care needs of heart failure patients. Moreover, the characteristics of the care environment pose challenges to providing cost-effective quality of care in a coordinated manner. In addition to the internal departments, several external parties such as primary care provider (PCP) offices are affiliated with this health system to coordinate specialized or acute care of their patients. Patients with comorbidities and chronic conditions need to be seen by multiple clinics and care facilities. These facilities may have different levels of implementation success with their electronic medical record (EMR) systems and other systems for medical and business operations related records. Thus, information may come from different sources and coordinating care delivery through effective communication among the care providers is very complex and challenging.

Coordinating care for HF patient can improve the cost and quality of care provided in health systems for these patients. Transitional care programs are actions designed to coordinate the continuity of healthcare as patients care extends across care facilities. We used a multimethod qualitative approach to investigate the patient flow along the continuum of care for patients with heart failure and identify the interventions that help to improve the cost and quality of care. We conducted a single case research and through text mining and workflow analysis revealed the characteristics of errors and opportunities to improve care process of HF patients through transitional care clinics, where errors can be identified and rectified before discharge.

CHAPTER IV

ESSAY 2_EMPIRICAL INVESTIGATION OF IMPACTFUL INTERVENTIONS

4.1. Introduction

The Patient Protection and Affordable Care Act (ACA) of 2010, encourages care providers to make data available to researchers in an effort to motivate research that focusses on the identification of ways to improve the quality of care delivered to patients and reduces the cost of care for hospitals. ACA requires that all hospitals implement electronic medical record (EMR) technologies that create electronic records of multiple aspects of the patient care process, including both clinical and administrative processes. These data become available for various government agencies, both federal and state as well as multiple related agencies. Thus, the ACA creates an opportunity for researchers to investigate and identify utility from patterns and relationships hidden in health care data to investigate the impact of interventions on the cost and quality of care.

For example, Helm, Alaedini, Stauffer, Bretthauer, and Skolarus (2015) used publicly available data to enhance the available empirical prediction methods to reduce hospital readmissions and optimize hospital resource allocation decisions, which is a critical and perennial problem in the operations and management systems and the health systems literature. Xiao et al., (2015) utilize over six years of data to identify economic and operational measures that can reduce readmissions in hospitals. Research investigation and empirical validation of the efficacy and impact of clinical and administrative interventions makes significant contribution to informing clinical and administrative strategies and processing that can improve the quality of care while simultaneously controlling costs. My comprehensive analysis of much similar research demonstrates that this is a useful research endeavor. In this study, I will empirically test the impact of transitional care and transitional care clinics (TCC), explained in Essay 1 in chapter 3, on the cost and quality of care measures that are identified in the first study.

4.2. Data Selection and Preparation

For this study, I use data from insurance claims data of heart failure patients that are served by two hospitals – one with and one without a transitional care clinic for heart failure patients. Our data covers all inpatient and outpatient claims of patients who are employees of the State of North Carolina and have filed a medical insurance claim related to their chronic heart failure condition between January 1, 2009 through December 31, 2014. Our data includes both inpatient services performed in the hospital as well as emergency room visits.

The data is organized by claims. Each row of data is a *claim* line that represents a single clinical service that was provided for that patient at that visit. Each visit may, and typically does, have multiple services performed. Hence, multiple claim lines exist for each patient visit. A patient visit, in the health IT area is typically referred to as an *encounter*. An encounter ID is a unique number assigned to each patient for a specific set of services that are provided for a specific visit to the health care provider at a certain period of time. Therefore, an encounter ID allows us to group all claims that belong to the same encounter and investigate the set of services performed and the nature of those services. Our data includes both encounter ID and member ID for each claim. Additionally, an *episode of care* is the set of care processes that a healthcare provider provides to patients as it treats specific conditions or maladies for a patient. There are multiple definitions of an episode of care in the literature. The McGraw Hill Medical Dictionary (2002) defined an episode of care as "Managed care Healthcare services provided for a specific illness during a set time period". The Farlex Partner Medical Dictionary (2012) describes an episode of care as "all services provided to a patient with a medical problem within a specific period of time across a continuum of care in an integrated system". According to Segen's Medical dictionary (2011), an episode of care refers to "the care episode of an inpatient, outpatient, day case, day patient. Each episode is initiated by a referral (or re-referral) or admission, and is ended by a discharge". In this study we consider this definition of an episode of care where a specific set of services are provided for a patient in a single encounter. Using an encounter as the unit of analysis in this study allows us to focus the research investigation on the empirical identification of the impact of TCC as a management intervention to manage cost and improve the quality of care measures, such as readmission, hospital length of stay for inpatient claims as well as number of ER visits for outpatient claims. Higher levels of coordination are required for patients who suffer from multiple chronic health conditions, i.e., have a higher number of comorbidities. A patient may be diagnosed with and treated for a different combination of comorbidities in each inpatient or outpatient encounter at a health provider location. This may result in variances in the costs of care provided and in the measures of quality of care for providers with and without transitional care programs. Studying these differences across encounters allows the examination of the impact of the transitional care clinic on important cost and quality outcome measures. Therefore, we focus on encounters as the unit of analysis in this study.

In order to identify the appropriate study variables for each encounter, we merged all claims that belong to the same encounter and aggregated all costs for the claims made in that encounter. On average, there are approximately 15 claim for each encounter. The data contained several negative claim charges and duplicated claimed charges, that we eliminated as part of our data cleansing procedure. The cleaned encounter records are used in our empirical analysis. Table 1 breaks down the count for each hospital, with and without transitional care, as well as the claim type.

Table 3. Total Records with and without Transitional Care Clinic (TCC)

	Claim Type	
	Inpatient	Outpatient
Encounters at Hospital with TCC	1866	886
Encounters at Hospital without TCC	4232	2115
Totals	6098	3001

Our data include the International Classification of Diseases, ninth version Clinical Modification codes (ICD-9-CM) for the first five diagnoses made in each encounter. ICD-9-CMs are the U.S. health system's adaptation of the international ICD-9 standard list of alphanumeric codes used to describe diagnoses (www.cms.org). These standardized codes improve consistency among physicians in recording patient symptoms and diagnoses for the purposes of payer claims reimbursement and clinical research. Chronic heart failure is likely to be accompanied by a number of other comorbidities such as renal failure, diabetes and chronic pulmonary diseases. We use the Risk Adjustment and Hierarchical Condition Category (HCC) codes to identify the most frequent comorbidities for patients with heart failure. HCC coding is a payment model mandated by the Centers for Medicare and Medicaid Services (CMS) in 1997. This model of classification identifies individuals with serious or chronic illness and assigns a risk factor score to the person based upon a combination of the individual's health conditions and demographic details (MMRR, 2014). We adopt HCC version 2014 ICD-9-CM crosswalk to classify the comorbidities for patients with heart failure. We include the HCC for each encounter after merging the claim lines. We created dummy variables for the most frequent comorbidities based on HCCs and used them as control variables in our analysis.

We calculated patients' age at the time of discharge for each encounter based on patient's date of birth. We refer to this as the encounter's age. We controlled for encounter's age at the time of discharge in our analysis. We excluded newborns and deliveries from our data since they are not the focus of this study. Any patient younger than 36 years of age is considered as an outlier and excluded from the data to ensure that the sample represents the population of interest for this study.

We calculated the length of stay (LOS) for each inpatient encounter based on the admission date and discharge date. We used the first claim service start date as the surrogate for admission date and the last claim service end date as the surrogate for discharge date. LOS is defined as the number of patient days from admission to discharge for an encounter. Our data shows that in an average encounter, a patient spends about eight days in the hospital. The median length of stay for an encounter is five days. Our data has some extreme case where the patient stayed more than two hundred days in the hospital as well.

Our data include Member ID, which is a unique identifier of each patient and help us to uniquely identify a patient across encounters and across all service providers. In other words, a patient's member id makes it possible to obtain a patient's entire readmission history and enables us to study the pattern of patient care and clinical diagnosis received through time at multiple health provider locations.

We calculated the number of days from a discharge to the next admission date for each patient and created dummied for 30-day, 60-day and 90-day readmission for each encounter. Figure 10 shows the encounters that are included in this study.

Table 4 presents summary statistics of the characteristics of the treatment (Hospital with TCC) and control (Hospital without TCC) groups for both inpatient and outpatient claims between 2009 and 2014. Total columns represent the total number of encounters. The figure in parentheses represents the percentage ratio of those occurrences, out of the total number of encounters, that have the same claim type at the representative location.

The variance across the variables in the summary statistics table suggests that any raw differences in outcome variables between the treatment and control group must be interpreted with caution, since the differences could reflect none TCC related interventions and policies that may affect patients with some characteristics differently from patients with other characteristics. Therefore, methods that control for patients' demographic and comorbidity differences are critical to our analysis.

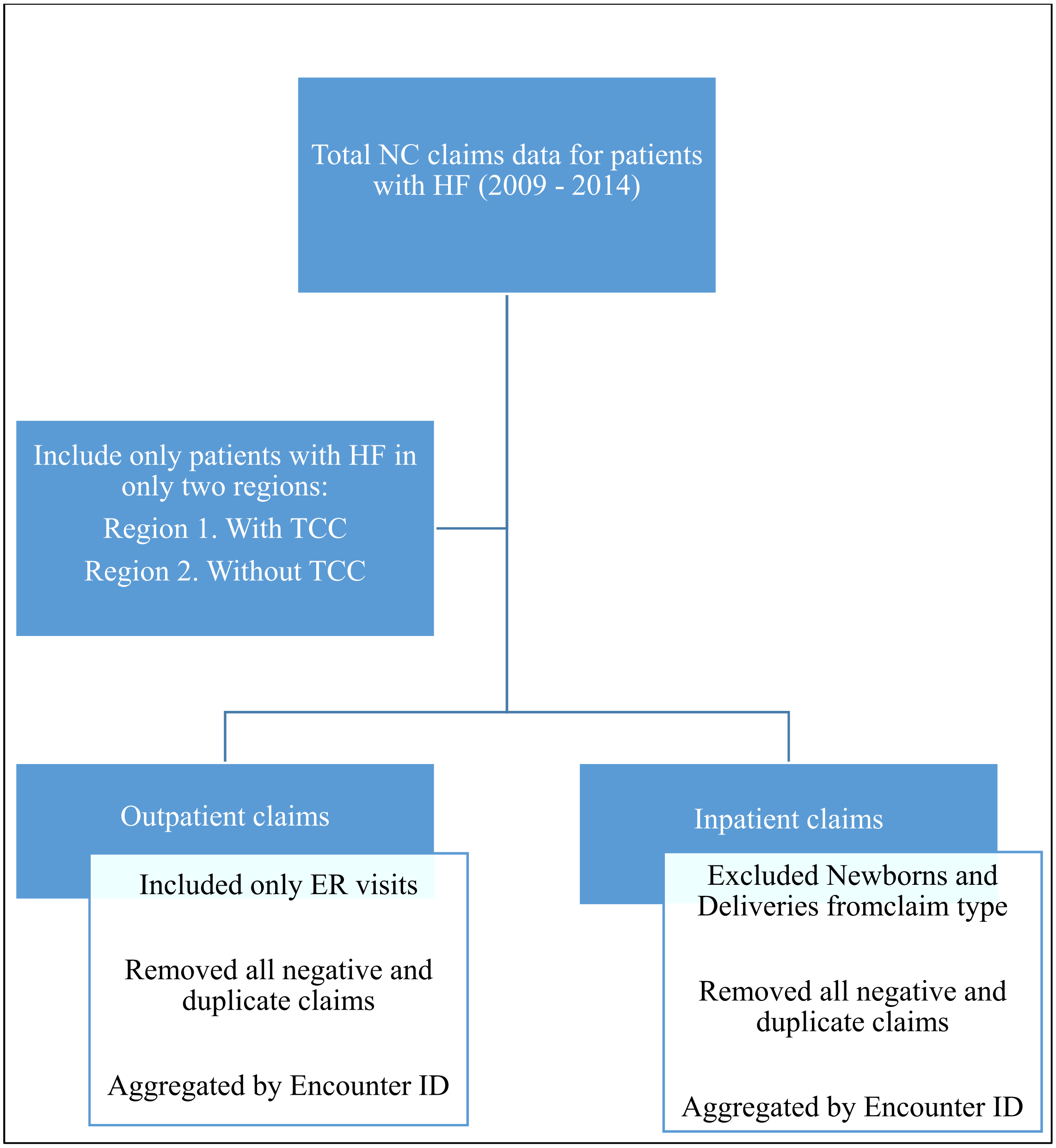


Figure 10. HF Encounters Included in Analysis

Table 4. Summary Statistics of Treatment and Control Group

	Group			
	Inpatient		**Outpatient**	
	Without TCC (%)	**With TCC (%)**	**Without TCC (%)**	**With TCC (%)**
Patient's Gender				
Male	1755 (41%)	785 (42%)	850 (41%)	343 (39%)
Female	2477 (59%)	1081 (58%)	1242 (59%)	539 (61%)
Comorbidity Variables				
Congestive Heart Failure	3835 (91%)	1686 (90%)	1749 (84%)	703 (80%)
Renal Failure	702 (17%)	338 (18%)	123 (6%)	33 (4%)
Specified Heart Arrhythmias	623 (15%)	260 (14%)	220 (11%)	69 (8%)
Cardio-Respiratory Failure and Shock	505 (12%)	293 (16%)	56 (3%)	36 (4%)
Diabetes	366 (9%)	198 (11%)	425 (20%)	212 (24%)
Chronic Obstructive Pulmonary Disease	302 (7%)	163 (9%)	88 (4%)	45 (5%)
Malnutrition and Obesity	247 (6%)	78 (4%)	13 (1%)	14 (2%)
Acute Myocardial Infarction	253 (6%)	91 (5%)	36 (2%)	4 (0.5%)
Septicemia, Sepsis	144 (3%)	86 (5%)	3 (0.1%)	5 (1%)
Cancer	134 (3%)	48 (3%)	36 (2%)	11 (1%)
Vascular Diseases	127 (3%)	54 (3%)	22 (1%)	13 (1%)
Ischemic Strokes	102 (2%)	24 (1%)	6 (0.3%)	5 (1%)
Hematological and Immunity Disorders	64 (2%)	55 (3%)	19 (1%)	7 (1%)
Head and Hip Fractures	91 (2%)	27 (1%)	15 (1%)	7 (1%)
Hemiplegia/Hemiparesis	91 (2%)	25 (1%)	6 (0.3%)	0 (0%)
Unstable Angina	82 (2%)	29 (2%)	27 (1%)	25 (3%)
Aspiration and Bacterial Pneumonias	67 (2%)	32 (2%)	1 (0.1%)	5 (1%)
Major Organ Transplant or Replacement	33 (1%)	18 (1%)	32 (2%)	8 (1%)
Encounter Characteristics	**Mean (Std. Dev.)**		**Mean (Std. Dev.)**	
Length of Stay	7.82 (9.75)	8.59 (12.88)	0.27 (0.70)	0.30 (0.76)
Encounter's Age	74.11 (12.72)	73.67 (12.50)	71.75 (13.22)	71.62 (12.63)

4.3. Difference-in-Differences Analysis

In this section we investigate the impact of transitional care clinic (TCC) as an intervention on cost and quality of care measures. Our data includes encounters from hospitals that serve two socio-economically similar regions in the state of North Carolina. One regional hospital implemented transitional care as a required egress mechanism for all HF patients, while the other one is considering the implementation of a transitional care policy for its HF patients, in the near future. We employ an ex post facto quasi experimental design in this study, shown in figure 2. We use the difference-in-differences method to study the impact of TCC as an intervention and identify its impact on all cause 30-day, 60-day and 90-day readmissions, heart failure 30-day, 60-day and 90-day readmissions, length of stay, total charges for inpatient encounters and number of ER visits for outpatient encounters between and across hospitals.

The difference-in-differences method applies two different degrees of variation sequentially so that spurious factors correlated with each degree of variation individually can be differenced away. Studies evaluating changes in outcomes associated with policy implementations need to control for background changes that occur with time. Meyer (1995) notes that the difference-in-differences approach is particularly applicable for these studies where the goal is to find variations in key explanatory exogenous variables, find comparison groups that are comparable and probe the implications of the hypotheses. A recent scientific statement from the American Heart Association, highlights the utility of the difference-in-differences approach to understand the relationships between clinical and administrative policy changes and the related subsequent outcomes by using a comparison group that is experiencing the same trends but is not exposed to the specific intervention (Dimick and Ryan, 2014).

To identify the difference-in-differences estimate, we need to run three different models for each outcome variable, as shown in the following models.

$$\textit{Model 1: } y_{it=\alpha+\gamma_0 D_{it}+\varepsilon_{it}}$$

$$\textit{Model 2: } y_{it=\alpha+\gamma_0 D_{it}+\gamma_1 t+\varepsilon_{it}}$$

$$\textit{Model 3: } y_{it=\alpha+\gamma_0 D_{it}+\gamma_1 t+\gamma_2 D_{iI}+\varepsilon_{it}}$$

Model 1 represents the effect of the treatment, which is the effect of the transitional care clinic in our study. Model 2 further examines the effect of time on the outcome variables. Model 3 includes the difference in differences estimate, which is the interaction of the effect of the treatment and time. These are shown in the following equations. In model 3, γ represents the difference in differences estimate.

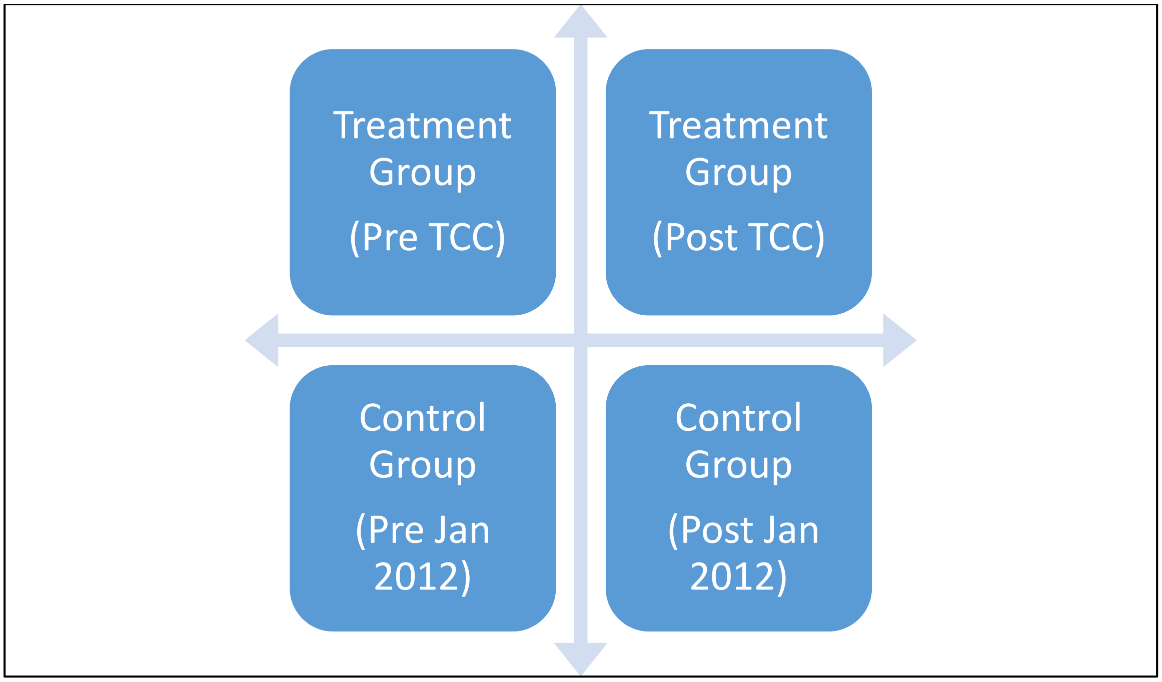


Figure 11. Ex Post Facto Quasi Experimental Design

The difference in differences is calculated by evaluating the outcome variable before and after the implementation of the intervention, represented as t=1 (after) and t=0 (before) in:

$$y_{i1} - y_{i0} = \delta + \gamma_2 D_{iI} + \varepsilon_i$$

Here, $y_{i1} - y_{i0}$ is the difference between the repeated outcome measures for each observation, D_{it} is the treatment indicator, γ_0 is the treatment effect and γ_1 is the effect of time on all units. ε_i is the difference between errors at time 1 and time 0, which is itself a normal random variate with mean equal to 0.

Two differences in outcomes are important:

1. The difference before and after the intervention in the group exposed to the intervention;

2. The difference before and after the policy change in the unexposed group.

We are interested in γ_2 value as the estimate of the difference in differences estimate.

4.3.1. Probit Model_ Base Model

Probit regression, often referred to as a probit model, is an effective means to model binary variables that have dichotomous outcomes. In the probit model, the inverse standard normal distribution of the probability is modeled as a linear combination of the predictors. It allows for the testing of hypotheses about the differences in the coefficients for the different levels of a variable. We apply probit as the appropriate method to test hypotheses related to the impact of TCC on our outcome variables. The hospital with TCC implemented this intervention in the beginning of January 2012. We used the following probit model to test the impact of TCC on nine outcome variables, including all cause 30-day, 60-day and 90-day readmissions, heart failure 30-day, 60-day and 90-day readmissions. Inpatient length of stay in hospital, total charges of all services provided during an encounter and number of ER visits. The encounters with heart failure that are served at hospital with TCC are considered treatment group while the encounters with heart failure that are served in hospital without TCC are considered control group. We test the impact of TCC across these two hospitals in the years before and after the implementation of this intervention.

We estimate the probit equations. All nine equations are listed below:

1. All cause 30-day readmission:

$P(ReAd30it{=}1) = \varphi(\alpha + \gamma_0 treatment_i + \gamma_1 postJan2012_t + \gamma_2 (treatment \times postJan2012)_{it})$

2. All cause 60-day readmission:

$P(ReAd60it{=}1) = \varphi(\alpha + \gamma_0 treatment_i + \gamma_1 postJan2012_t + \gamma_2 (treatment \times postJan2012)_{it})$

3. All cause 90-day readmission:

$P(ReAd90it{=}1) = \varphi(\alpha + \gamma_0 treatment_i + \gamma_1 postJan2012_t + \gamma_2 (treatment \times postJan2012)_{it})$

4. Heart Failure 30-day readmission:

$P(HFReAd30it{=}1) = \varphi(\alpha + \gamma_0 treatment_i + \gamma_1 postJan2012_t + \gamma_2 (treatment \times postJan2012)_{it})$

5. Heart Failure 60-day readmission:

$P(HFReAd60it=1) = \varphi(\alpha + \gamma_0 treatment_i + \gamma_1 postJan2012_t + \gamma_2 (treatment \times postJan2012)_{it})$

6. Heart Failure 90-day readmission:

$P(HFReAd90it=1) = \varphi(\alpha + \gamma_0 treatment_i + \gamma_1 postJan2012_t + \gamma_2 (treatment \times postJan2012)_{it})$

7. Inpatient Length of Stay:

$P(BinLOSit=1) = \varphi(\alpha + \gamma_0 treatment_i + \gamma_1 postJan2012_t + \gamma_2 (treatment \times postJan2012)_{it})$

8. Total Charges:

$P(BinCharges=1) = \varphi(\alpha + \gamma_0 treatment_i + \gamma_1 postJan2012_t + \gamma_2 (treatment \times postJan2012)_{it})$

9. Outpatient ER Visits:

$P(ERVisits=1) = \varphi(\alpha + \gamma_0 treatment_i + \gamma_1 postJan2012_t + \gamma_2 (treatment \times postJan2012)_{it})$

The Probit model is a binary classification model that requires the dependent variable to take only one of two values. In equation number 1, *ReAd30* is a dummy equal to one if a patient encounter is readmission within 30 days after that patient's previous discharge. We created dummies for all cause 60-day and 90-day readmissions as well as heart failure 30-day, 30-day and 90-day readmissions in the same way. We also created a dummy variable for inpatient length of stay as BinLOS shown in equation 7. If the duration of stay in the hospital for the encounter is equal to average five days or more BinLOS is equal to one. For total charges of all services provided during the same encounter, we consider a dummy variable named "BinCharges" presented in equation 8. We calculated the trimmed mean of total charges after excluding the extreme outliers. If the total of cost of the encounter is greater than the trimmed mean BinCharges is equal to one. In equation 9, we estimate the impact of TCC on encounters' ER visits. Therefore, we are interested in the ER encounters that have stayed in the hospital as inpatient encounters at some point of time before their ER visit. This way, we only consider those outpatient encounter in the treatment group that have gone through TCC at some point of time before their need to visit ER. In the control group, we are considering the outpatient ER visits that have been treated in the inpatient setting before their ER encounter. We created the ERVisits dummy variable that is equal to one if an inpatient encounter returns to the ER.

The *Treatment* variable is a dummy equal to one for the encounters that are visited in the hospital with TCC. We expect γ_0 to be negative if TCC lead to reduction in outcome variable. For example in equation one, a negative value of γ_0 implies a lower 30-day readmission rates for treatment group after TCC implementation.

PostJan2012 is a dummy equal to one for any encounter visit after January 2012. Thus, γ_1 reflects the average change in 30-day readmission rates for both treatment and control group between January 2012 and December 2014.

The test of the impact of TCC that was initiated in January 2012 reflects on γ_2 which is the coefficient on the interaction term between TCC treatment and PostJan2012 variables. Negative γ_2 values imply that the TCC implementation resulted in reducing the outcome variable. For example in equation one negative value of γ_2 will refer to reduction in 30-day readmission rates for treatment group after TCC implementation.

Since probit model is not a linear model, we need to be cautious about interpretation of the regression coefficients. The coefficient cannot be directly used as marginal effects. As explained earlier, the treatment effect variable (*treatment* × *PostJan2012* Interaction) is a discrete variable. We calculate the effect of TCC by predicting two probabilities of outcome measure, one with interaction variable set equal to one and the other with the interaction term set equal to zero. The treatment effect is the average of the difference in the two probabilities of outcome measure. The third column in table 5, presents the average marginal effect of TCC for each outcome measure. We are interested on the marginal effect of the interaction term for each outcome variable.

The model estimates from a probit regression model are maximum likelihood estimates that are not calculated to minimize variance. Therefore, the ordinary least squares (OLS) R^2 approach to goodness-of-fit does not apply for probit model. To evaluate the goodness-of-fit of probit models, several pseudo R^2 have been developed (Hagle & Mitchell, 1992). Menard (2000), in a study comparing five distinct pseudo R^2 indices, concluded that McFadden's index was preferred due to both its conceptual similarity to OLS R^2, as used in linear regression, and due to its relative independence of the base rate of the binary outcome variable. In calculating the McFadden pseudo R^2, the log likelihood of the intercept model is treated as a total sum of squares, and the log likelihood of the full model is treated as the sum of squared errors. The ratio of the likelihoods suggests the level of improvement over the intercept model offered by the full model. If a model has a very low likelihood, then the log of the likelihood will have a larger magnitude than the log of a more likely model. Thus, a small ratio of log likelihoods indicates that the full model is a far better fit than the intercept model. If comparing two models on the same data, McFadden's would be higher for the model with the greater likelihood. McFadden's pseudo R-squared ranging from 0.2 to 0.4 indicates very good model fit (McFadden, 1974). We use McFadden's R^2 to assess and compare the goodness-of-fit for various probit models. McFadden's R^2 values are presented in the last column of table 5.

Table 5. Probit Results: HF Patients with TCC vs. without TCC

	Coefficients	Std. Err.	TCC effect	McFadden Pseudo R^2
A. All cause 30-day readmission				0.001
Treatment (γ_0)	-0.072	0.060	-0.013	
PostJan2012 (γ_1)	-0.047	0.050	-0.011	
Treatment x PostJan2012 (γ_2)	-0.026	0.090	-0.006	
B. All cause 60-day readmission				0.002
Treatment (γ_0)	0.011	0.090	0.006	
PostJan2012 (γ_1)	-0.035	0.090	-0.002	
Treatment x PostJan2012 (γ_2)	0.004	0.150	0.000	
C. All cause 90-day readmission				0.001
Treatment (γ_0)	0.063	0.091	0.005	
PostJan2012 (γ_1)	-0.005	0.076	0.000	
Treatment x PostJan2012 (γ_2)	0.015	0.132	0.001	
D. HF 30-day readmission				0.004
Treatment (γ_0)	-0.090	0.087	-0.007	
PostJan2012 (γ_1)	-0.160	0.080	-0.012	
Treatment x PostJan2012 (γ_2)	-0.105	0.130	-0.008	
E. HF 60-day readmission				0.006
Treatment (γ_0)	0.027	0.138	0.006	
PostJan2012 (γ_1)	0.028	0.132	0.001	
Treatment x PostJan2012 (γ_2)	-0.023	0.214	-0.005	
F. HF 90-day readmission				0.004
Treatment (γ_0)	0.088	0.129	0.003	
PostJan2012 (γ_1)	-0.129	0.121	-0.004	
Treatment x PostJan2012 (γ_2)	0.085	0.196	0.002	
G. Length of Stay				0.001
Treatment (γ_0)	0.092	0.049	0.036	
PostJan2012 (γ_1)	0.014	0.039	0.006	
Treatment x PostJan2012 (γ_2)	-0.027	0.070	-0.011	
H. Total Charges				0.007
Treatment (γ_0)	0.046	0.053	0.015	
PostJan2012 (γ_1)	0.234	0.042	0.078	
Treatment x PostJan2012 (γ_2)	0.005	0.074	0.002	

	Coefficients	Std. Err.	TCC effect	McFadden Pseudo R^2
I. ER visits				0.009
Treatment (γ_0)	-0.150	0.106	-0.15	
PostJan2012 (γ_1)	0.039	0.088	0.04	
Treatment x PostJan2012 (γ_2)	-0.032	0.162	-0.03	

The estimated coefficients for all cause 60-day and 90-day readmissions as well as heart failure 60-day and 90-day readmissions are small in magnitude and insignificant. This suggests that there is there is no variation in overall trends of 60-day and 90-day readmissions for both groups after TCC implementation. However, the average marginal treatment effect shows that implementation of TCC intervention lead to about 1% reduction in both all cause and heart failure 30-day readmissions as well as inpatient length of stay. Table 5 also shows significant marginal effect of TCC implementation in reducing the ER visits by 3%. These are used to test the associated hypotheses shown in Table 5a.

Table 5a. Hypothesis Testing of Probit Results: HF Patients with TCC (Treatment Group) vs. without TCC (Control Group)

Hypothesis 1	The transitional care clinic has a significant effect on reducing 30-Day Heart-Failure Readmissions in the treatment group. (significant within group difference)	Supported
Hypothesis 2	The transitional care clinic has a significant effect on reducing 30-Day Heart-Failure Readmissions between the treatment and control group. (significant between group difference)	Supported
Hypothesis 3	The transitional care clinic has a significant effect on reducing 60-Day Heart-Failure Readmissions in	Not Supported

	the treatment group. (significant within group difference)	
Hypothesis 4	The transitional care clinic has a significant effect on reducing 60-Day Heart-Failure Readmissions between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 5	The transitional care clinic has a significant effect on reducing 90-Day Heart-Failure Readmissions in the treatment group. (significant within group difference)	Not Supported
Hypothesis 6	The transitional care clinic has a significant effect on reducing 90-Day Heart-Failure Readmissions between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 7	The transitional care clinic has a significant effect on reducing 30-Day All Cause Readmissions in the treatment group. (significant within group difference)	Supported
Hypothesis 8	The transitional care clinic has a significant effect on reducing 30-Day All Cause Readmissions between the treatment and control group. (significant between group difference)	Supported
Hypothesis 9	The transitional care clinic has a significant effect on reducing 60-Day All Cause Readmissions in the treatment group. (significant within group difference)	Not Supported
Hypothesis 10	The transitional care clinic has a significant effect on reducing 60-Day All Cause Readmissions between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 11	The transitional care clinic has a significant effect on reducing 90-Day All Cause Readmissions in the treatment group. (significant within group difference)	Not Supported
Hypothesis 12	The transitional care clinic has a significant effect on reducing 90-Day All Cause Readmissions between the treatment and control group. (significant between group difference)	Not Supported

Hypothesis 13	The transitional care clinic has a significant effect on reducing length of stay in the treatment group. (significant within group difference)	Supported
Hypothesis 14	The transitional care clinic has a significant effect on reducing length of stay between the treatment and control group. (significant between group difference)	Supported
Hypothesis 15	The transitional care clinic has a significant effect on reducing total cost of care in the treatment group. (significant within group difference)	Not Supported
Hypothesis 16	The transitional care clinic has a significant effect on reducing total cost of care between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 17	The transitional care clinic has a significant effect on reducing ER visits for patients with previous inpatient encounters in the treatment group. (significant within group difference)	Supported
Hypothesis 18	The transitional care clinic has a significant effect on reducing ER visits for patients with previous inpatient encounters between the treatment and control group. (significant between group difference)	Supported

It is important to note that in this set of analyses, we have not controlled for demographic and other observable patient characteristics. Therefore, we expect to observe low pseudo R^2 values. Since the encounters in the treatment and control group differ in terms of demographic characteristics and comorbidities and severity of their disease, the observed differences in outcome measures might be affected and reflect the underlying differences between the treatment and control group instead of the impact of the proposed intervention. Therefore, it is important to control for demographic and other encounters' observable characteristics in using the difference-in-differences approach.

Controlling for theses variables will reduce the residual variance of the regression model and lead to providing more efficient estimates.

In the next section we develop and discuss probit models controlling for encounters' observable variables such as demographics and comorbidities to reduce the probability of false treatment effect and the chance of unknown shocks beyond TCC intervention that may influence encounters with different characteristics.

4.3.2. Probit Model_ Controlled for Encounters' Characteristics

In this section we consider the demographic characteristics differences between the encounters visited in the treatment group and the control group, to make sure that the observed differences in outcome measures reflect the effect of the TCC intervention rather than underlying differences between the treatment and the control group. Controlling for observable variables such as demographics and comorbidities in this study will reduce the residual variances and provide more efficient estimates in the probit model. Therefore, in this section we rewrite the probit equations from the general model in order to control for encounter characteristics in the following manner:

(10) $P(OutcomeMeasure=1) = \varphi(\alpha+\beta \boldsymbol{Y_{it}} + \gamma_0 treatment_i + \gamma_1 postJan2012_t + \gamma_2 (treatment \times postJan2012)_{it})$

Where, $\boldsymbol{Y_{it}}$ is a vector that includes encounter's age at the time of services, encounter's gender, as well as dummy variables for most frequent comorbidities based on the Risk Adjustment and Hierarchical Condition Category (HCC) codes provided by CMS (Kautter, Pope et al, 2014). These variables control for observable differences in the characteristics of the treatment and control group that affect out outcome variables beyond the impact of TCC implementation.

In equation 10, unobservable differences will be identified by the *treatment* variable. In this model, once again the *treatment* variable is a dummy equal to one for the encounters that are visited in the hospital with TCC. We also include *PostJan2012* variable as a dummy equal to one for any encounter visit after January 2012. To capture the impact of the TCC we have to include the interaction term between *treatment* and *PostJan2012*. γ_2 represents the impact of TCC that was initiated in January 2012. We replace the *OutcomeMeasure* dependent variable in equation 10 by each of the outcome variables presented in equations 1 to 9 in section 4.2.2 to identify the impact of TCC on those variables.

Table 6 presents the results of probit model controlling for encounters' demographic characteristics and comorbidities for all cause 30-day, 60-day and 90-day readmissions. the first column in table 4 shows the coefficients of the control variables as well as treatment impact on all cause 30-day readmission. The coefficients of *treatment* and *PostJan2012* are both small in magnitude and insignificant. This corresponds with our finding in section 4.2.2, where we did not include the demographics and comorbidities. This suggests that the there is no overall trend change in all-cause 30-day readmission in terms of the control variables for the two (treatment and control) groups.

The fact that γ_0 remains significant in this model, suggests that TCC implementation reduces all cause 30-day readmission even after controlling for demographics and comorbidities. The treatment effect after January 2012 (γ_2), does not change when we include demographics in the model. This suggests that any changes in demographic and comorbidities composition of the treatment and control group that occurred over time are uncorrelated with the treatment.

Significant coefficients on other control variables are show with an asterisk (*). The overall TCC effect on all cause 30-day readmissions is presented in the last row, indicates that the TCC implementation reduces all-cause 30-day readmissions by 7%. Older encounters have higher probability of all cause 30-day readmissions. Encounter with congestive heart failure, Chronic Obstructive Pulmonary Disease (COPD) and Septicemia/Sepsis have higher likelihood of all cause 30-day readmission. Table 4 shows that after controlling for demographic characteristics and comorbidities, all-cause 60-day readmissions reduces about 4% after implementation of TCC. The coefficients for 90-day readmissions are not significant and we do not observe significant changes even after controlling for demographics and comorbidities of the encounters.

Table 6. Probit Results: All Cause Readmissions _Controlled for Encounter Characteristics

Variables	**All Cause 30-Day Readmission**	**All Cause 60-Day Readmission**	**All Cause 90-Day Readmission**
Age	0.39 (0.15) *	0.49 (0.23) *	-0.62 (0.24) *
Gender	0.01 (0.04)	0.08 (0.07)	-0.06 (0.06)

Variables	**All Cause 30-Day Readmission**	**All Cause 60-Day Readmission**	**All Cause 90-Day Readmission**
Congestive Heart Failure	0.57 (0.06) *	0.01 (0.12)	0.02 (0.11)
Renal Failure	0.24 (0.06) *	-0.15 (0.1)	0.35 (0.07) *
Specified Heart Arrhythmias	0.22 (0.06) *	-0.18 (0.12)	0.11 (0.09)
Cardio-Respiratory Failure and Shock	0.11 (0.07)	-0.06 (0.11)	0.08 (0.09)
Diabetes	0.19 (0.07) *	-0.14 (0.13)	0 (0.11)
Chronic Obstructive Pulmonary Disease	0.54 (0.1) *	0.09 (0.13)	0.08 (0.11)
Malnutrition and Obesity	0.41 (0.11) *	0.19 (0.13)	0.3 (0.12) *
Acute Myocardial Infarction	0.97 (0.16) *	-0.31 (0.2)	-0.02 (0.14)
Septicemia/ Sepsis	0.56 (0.14) *	0.15 (0.18)	-0.07 (0.18)
Cancer	0.44 (0.15) *	-0.06 (0.22)	0.19 (0.17)
Vascular Diseases	0.07 (0.12)	0.08 (0.2)	0.24 (0.16)
Ischemic Strokes	0.29 (0.16) *	-0.15 (0.3)	-0.16 (0.25)
Hematological and Immunity Disorders	0.04 (0.15)	-0.47 (0.37)	-0.08 (0.23)
Head and Hip fractures	0.14 (0.15)	0.08 (0.25)	-0.24 (0.29)
Hemiplegia/Hemiparesis	0 (0.15)	-0.06 (0.29)	0.28 (0.21)
Unstable Angina	-0.04 (0.15)	-0.41 (0.37)	0 (0.25)
Aspiration and Pneumonias	0.09 (0.16)	-3.46 (0.59)	-3.64 (0.59)
Major Organ Transplant or Replacement	0.22 (0.2)	0.42 (0.29)	0.09 (0.33)
Treatment (γ_0)	-0.08 (0.06)*	0.12 (0.1)	0.06 (0.09)
PostJan2012 (γ_1)	-0.02 (0.05)	-0.06 (0.09)	-0.01 (0.08)
Treatment × PostJan2012 (γ_2)	-0.03 (0.09)	0 (0.15)	0.04 (0.13)
Pseudo R^2	0.08	0.05	0.03
TCC effect	-0.07	-0.04	0.003

Similarly, we analyzed HF Readmissions using the probit model discussed above and shown in equation 10.

Table 7 presents the results of probit model controlling for encounters' demographic characteristics and comorbidities for 30-day, 60-day and 90-day heart failure readmissions. Heart failure readmission refers to encounters that return to hospital and admitted with the primary diagnosis of heart failure. The first column in table 7 shows the coefficients of the control variables as well as treatment impact on heart failure 30-day readmission.

There is no significant difference between coefficient of *Treatment* and *PostJan2102* between the model that does control for encounter characteristics and the model that does not. This suggests that the there is no overall trend change in heart failure 30-day readmission in terms of the control variables for the two groups, treatment and control. The fact that γ_1 remain significant in this model, suggests that HF 30-day readmission reduced significantly after January 2012 even after controlling for demographics and comorbidities. Interestingly, the overall TCC effect on heart failure 30-day readmissions is significant after controlling for encounter characteristics. Our analysis shows that TCC implementation reduces heart failure 30-day readmissions by 20%. This is presented in the last row of column one in table 7. Significant coefficients on other control variables are show with an asterisk (*). Older encounters have higher probability of heart failure 30-day readmissions. Encounters with specified heart arrhythmias, chronic obstructive pulmonary disease, acute myocardial infarction and Septicemia/Sepsis have higher chance of heart failure 30-day readmission.

Table 7 shows that after controlling for demographic characteristics and comorbidities heart failure 60-day readmissions reduces about 4% after implementation of TCC. The coefficients for 90-day readmissions are not significant and we do not observe significant changes even after controlling for demographics and comorbidities of the encounters.

Table 7. Probit Results: HF Readmissions _Controlled for Encounter Characteristics

Variables	HF 30-Day Readmission	HF 60-Day Readmission	HF 90-Day Readmission
Age	0.77 (0.29) *	0.94 (0.39) *	-0.5 (0.37)
Gender	-0.05 (0.07)	0.19 (0.12)	-0.08 (0.1)
Congestive Heart Failure	4.5 (0.96)	4.0 (0.15)	3.95 (0.15)
Renal Failure	0.14 (0.09)	0.65 (0.25) *	0.29 (0.11) *
Specified Heart Arrhythmias	0.41 (0.11) *	-0.3 (0.19)	0.09 (0.13)
Cardio-Respiratory Failure and Shock	0.15 (0.11)	0.05 (0.16)	0.2 (0.13)
Diabetes	0.04 (0.11)	-0.14 (0.2)	-0.04 (0.18)
Chronic Obstructive Pulmonary Disease	0.55 (0.18) *	0.19 (0.18)	-0.12 (0.19)
Malnutrition and Obesity	0.49 (0.2) *	0.07 (0.21)	0.28 (0.17)
Acute Myocardial Infarction	0.77 (0.25) *	-0.41 (0.19)	-3.92 (0.21)
Septicemia/ Sepsis	0.81 (0.33) *	-0.19 (0.37)	-3.9 (0.25)
Cancer	0.59 (0.28) *	-0.2 (0.38)	0.01 (0.29)
Vascular Diseases	0.2 (0.2)	-0.39 (0.27)	0.21 (0.24)
Ischemic Strokes	0.44 (0.21)	-0.32 (0.33)	-3.96 (0.34)
Hematological and Immunity Disorders	0.39 (0.18) *	0.04 (0.39)	0.11 (0.31)
Head and Hip fractures	0.45 (0.22)	-0.38 (0.35)	-3.9 (0.36)
Hemiplegia/Hemiparesis	0.33 (0.22)	0.17 (0.39)	0.37 (0.33)
Unstable Angina	-0.3 (0.26)	-0.39 (0.36)	-0.04 (0.39)
Aspiration and Pneumonias	-0.47 (0.4)	-0.38 (0.36)	-3.9 (0.37)
Major Organ Transplant or Replacement	-0.07 (0.42)	-0.38 (0.50)	-3.81 (0.52)
Treatment (γ_0)	-0.16 (0.08) *	-0.3 (0.15) *	-0.14 (0.13)
PostJan2012 (γ_1)	0.08 (0.09)	0.04 (0.14)	0.07 (0.14)
Treatment × PostJan2012 (γ_2)	-0.14 (0.14) *	-0.29 (0.23)	0.11 (0.21)
Pseudo R^2	0.09	0.11	0.07
TCC effect	-0.20	-0.04	0.00

Table 8 presents the results of probit model controlling for encounters' demographic characteristics and comorbidities for other cost and quality of care measures such as inpatient length of stay, cost of all services provided during an encounter as well as ER visits for patients with a history of heart failure. The first column in table 8 shows the coefficients of the control variables as well as treatment impact on encounters average length of stay in hospital for inpatient claims. There is little change in γ_0 coefficient from 0.09 to 0.11 with standard error of 0.05. This suggests that encounters' comorbidities and demographic composition between the treatment and control group have significant impact on the encounters length of stay in hospital. The interaction effect (γ_2) also remains significant and varies from -0.02 to -0.05. This also suggests the impact of comorbidities and demographic differences on encounters' length of stay in hospital changes between the two groups. The overall TCC effect on encounters length of stay is significant after controlling for encounter characteristics. Our analysis shows that TCC implementation reduces average length of stay by 2%. This is presented in the last row of column one in table 8. Significant coefficients on other control variables are shown with an asterisk (*). Encounter age does not reveal any significant impact on probability of staying longer in the hospital. On average encounters with Cardio-Respiratory Failure and Shock, Septicemia/Sepsis, Head and Hip Fractures, and Aspiration and Pneumonias significantly have higher chance of higher length of stay in the hospital.

The second column in table 8 shows the coefficients of the control variables as well as treatment impact on total service charges of encounters in hospital for inpatient claims. Interestingly, the *treatment*, *PostJan2012* and the interaction effect coefficients change after controlling for encounter characteristics. This suggests that encounters comorbidities and demographic composition between the treatment and control group have significant impact on the cost of services provided during each encounter. The overall TCC effect on encounters total charges is significant after controlling for encounter characteristics. Our analysis shows that TCC implementation reduces costs by 1%. Older encounters have higher probability of incurring higher charges. Encounter gender does not show any significant impact on charges. Encounters with Cardio-Respiratory Failure and Shock, Acute Myocardial Infarction, Septicemia/Sepsis, Head and Hip Fractures, and Aspiration and Pneumonias, and Major Organ Transplant or Replacement have significantly higher chance of higher costs in the hospital.

The third column in table 8 shows the coefficients of the control variables as well as treatment impact on ER visits of encounters that have been visited in the inpatient setting before their ER incident. In this case also we observe that the *treatment*, *PostJan2012* and the interaction effect coefficients changes after controlling for encounters characteristics. This suggests that encounters comorbidities and demographic composition between the treatment and control group have significant impact on patients returning to ER after discharge from inpatient setting. The overall TCC effect on encounters ER visits is significant after controlling for encounter characteristics. This is presented in the last row of the third column in table 8. Significant coefficients on other control variables are show with an asterisk (*). Our analysis shows that TCC implementation reduces ER visits by 5%.

We did not find any significant influence of encounters' age and gender on ER visits. However, there are differences in terms of encounters comorbidity compositions. Encounters with renal failure, Acute Myocardial Infarction, and Aspiration and Pneumonias, and vascular disease have significantly higher chance of returning to ER.

Table 8. Probit Results: Length of Stay, Costs and ER Visits_ Controlled for Encounter Characteristics

Variables	**Length of Stay**	**Total Charges**	**ER visits**
Age	-0.09 (0.12)	-0.39 (0.14) *	0 (0)
Gender	0.08 (0.03) *	0 (0.04)	0 (0.05)
Congestive Heart Failure	0.28 (0.06) *	0.25 (0.07) *	0.01 (0.06)
Renal Failure	0.21 (0.04) *	0.42 (0.05) *	0.21 (0.11) *
Specified Heart Arrhythmias	-0.04 (0.05)	0.29 (0.05) *	0.1 (0.08)
Cardio-Respiratory Failure/ Shock	0.31 (0.05) *	0.52 (0.05) *	0.2 (0.14)
Diabetes	-0.1 (0.06) *	-0.3 (0.07) *	0.04 (0.06)
Chronic Obstructive Pulmonary Disease	-0.17 (0.06) *	-0.14 (0.07) *	0.13 (0.12)
Malnutrition and Obesity	0.06 (0.07)	0.08 (0.08)	-0.15 (0.26)
Acute Myocardial Infarction	0.06 (0.07)	0.95 (0.07) *	0.45 (0.24) *
Septicemia, Sepsis	0.44 (0.09) *	0.77 (0.09) *	-0.17 (0.48)
Cancer	0.15 (0.1)	0.31 (0.1) *	0.4 (0.19) *
Vascular Diseases	0.22 (0.1) *	0.31 (0.1) *	0.38 (0.22) *
Ischemic Strokes	0.24 (0.12) *	0.45 (0.12) *	0.45 (0.38)
Hematological and Immunity Disorders	-0.12 (0.12)	0.03 (0.13)	0.39 (0.29)
Head and Hip Fractures	0.63 (0.13) *	0.82 (0.12) *	-0.21 (0.3)
Hemiplegia/Hemiparesis	0.2 (0.12)	-0.17 (0.15)	-0.5 (0.61)
Unstable Angina	-0.34 (0.13) *	-0.01 (0.14)	-0.27 (0.2)
Aspiration and Pneumonias	0.57 (0.14) *	0.7 (0.14) *	0.95 (0.53) *
Major Organ Transplant	0.04 (0.18)	0.33 (0.19) *	0.01 (0.21)
Treatment (γ_0)	0.11 (0.05) *	0.07 (0.06)	-0.08 (0.07)
PostJan2012 (γ_1)	0.01 (0.04)	0.18 (0.04) *	-0.09 (0.06)
Treatment × PostJan2012 (γ_2)	-0.05 (0.07)	-0.02 (0.08)	0.02 (0.11)*
Pseudo R^2	0.05	0.12	0.01

Variables	Length of Stay	Total Charges	ER visits
TCC effect	-0.02	-0.01	-0.05

Table 8a shows the results of hypothesis testing on the probit results after controlling for the demographic and co-morbidity characteristics of encounters.

Table 8a. Hypothesis Testing of Probit Results: HF Patients with TCC vs. without TCC Controlling for Encounter Characteristics

Hypothesis 1	The transitional care clinic has a significant effect on reducing 30-Day Heart-Failure Readmissions in the treatment group. (significant within group difference)	Supported
Hypothesis 2	The transitional care clinic has a significant effect on reducing 30-Day Heart-Failure Readmissions between the treatment and control group. (significant between group difference)	Supported
Hypothesis 3	The transitional care clinic has a significant effect on reducing 60-Day Heart-Failure Readmissions in the treatment group. (significant within group difference)	Supported
Hypothesis 4	The transitional care clinic has a significant effect on reducing 60-Day Heart-Failure Readmissions between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 5	The transitional care clinic has a significant effect on reducing 90-Day Heart-Failure Readmissions in the treatment group. (significant within group difference)	Not Supported
Hypothesis 6	The transitional care clinic has a significant effect on reducing 90-Day Heart-Failure Readmissions between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 7	The transitional care clinic has a significant effect on reducing 30-Day All Cause Readmissions in the treatment group. (significant within group difference)	Supported
Hypothesis 8	The transitional care clinic has a significant effect on reducing 30-Day All Cause Readmissions between the	Supported

	treatment and control group. (significant between group difference)	
Hypothesis 9	The transitional care clinic has a significant effect on reducing 60-Day All Cause Readmissions in the treatment group. (significant within group difference)	Supported
Hypothesis 10	The transitional care clinic has a significant effect on reducing 60-Day All Cause Readmissions between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 11	The transitional care clinic has a significant effect on reducing 90-Day All Cause Readmissions in the treatment group. (significant within group difference)	Not Supported
Hypothesis 12	The transitional care clinic has a significant effect on reducing 90-Day All Cause Readmissions between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 13	The transitional care clinic has a significant effect on reducing length of stay in the treatment group. (significant within group difference)	Not Supported
Hypothesis 14	The transitional care clinic has a significant effect on reducing length of stay between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 15	The transitional care clinic has a significant effect on reducing total cost of care in the treatment group. (significant within group difference)	Not Supported
Hypothesis 16	The transitional care clinic has a significant effect on reducing total cost of care between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 17	The transitional care clinic has a significant effect on reducing ER visits for patients with previous inpatient encounters in the treatment group. (significant within group difference)	Supported
Hypothesis 18	The transitional care clinic has a significant effect on reducing ER visits for patients with previous inpatient encounters between the treatment and control group. (significant between group difference)	Supported

4.3.3. Probit Model_ Controlled for Encounters' Characteristics_ Annual Effect

In section 4.3.2, we identified the impact of TCC on cost and quality of care outcome measures and controlled our results based on encounters' age and gender as well as their comorbidity compositions. Using the probit model, we compared the effect of TCC before and after January 2012 to identify and test the changes in outcome measures. In this section, we include the interaction terms of the treatment with year dummies for 2012, 2013 and 2014.

By interacting the treatment term with year dummies we are able to reduce the chance of misinterpreting the impact of TCC for any unknown external influence that may affect the encounters with different demographic and comorbidity composition in the treatment group and present as an outcome. Table 9 shows the coefficients of probit model including the year dummy variables for all cost and quality of care measures explained in section 4.3.2. We observe that all cause 30-day readmissions reduced about 4%, even after controlling for demographic, comorbidities and year dummies in both 2013 and 2014 for the treatment group. We also observe a significant annual reduction in heart failure 30-day readmissions of 2%, 3% and 8% in the years 2012, 2013 and 2014 respectively for the treatment group. Another interesting finding is that the ER visits reduce by 7% and 11% in years 2013 and 2014 respectively for the treatment group. Therefore, impact of TCC on all cause 30-day readmissions, heart failure 30-day readmissions and ER visits are significant even after controlling for annual changes. We could not find any significant annual changes in other outcome variables.

Table 9. Probit Results: Separate Year Interactions

	Coefficients	Std. Err.	TCC Effect	Pseudo R^2
A. All cause 30-day readmission				0.08
Treatment x 2012	0.07	0.09	0.01	
Treatment x 2013	-0.02	0.08	-0.04	
Treatment x 2014	-0.02	0.12	-0.04	
B. All cause 60-day readmission				0.05
Treatment x 2012	0.11	0.15	-0.01	
Treatment x 2013	0.00	0.15	-0.02	
Treatment x 2014	0.08	0.18	-0.04	
C. All cause 90-day readmission				0.03
Treatment x 2012	0.19	0.12	0.01	
Treatment x 2013	-0.01	0.13	0.00	
Treatment x 2014	0.00	0.18	0.00	
D. HF 30-day readmission				0.08
Treatment x 2012	0.21	0.13	-0.02	
Treatment x 2013	-0.04	0.14	-0.03	
Treatment x 2014	0.11	0.17	-0.08	
E. HF 60-day readmission				0.11
Treatment x 2012	0.07	0.24	0.00	
Treatment x 2013	-0.24	0.28	0.00	
Treatment x 2014	0.06	0.26	0.00	
F. HF 90-day readmission				0.08
Treatment x 2012	0.20	0.18	0.01	
Treatment x 2013	0.15	0.18	0.00	
Treatment x 2014	-3.90	271.77	-0.11	
G. Length of Stay				0.04
Treatment x 2012	0.09	0.07	-0.03	
Treatment x 2013	0.03	0.07	0.01	
Treatment x 2014	0.01	0.09	0.00	

	Coefficients	Std. Err.	TCC Effect	Pseudo R^2
H. Total Charges				0.11
Treatment x 2012	0.10	0.08	0.03	
Treatment x 2013	0.18	0.07	0.05	
Treatment x 2014	0.21	0.10	0.06	
I. ER visits				0.05
Treatment x 2012	0.04	0.11	0.02	
Treatment x 2013	-0.19	0.11	-0.07	
Treatment x 2014	-0.32	0.20	-0.11	

4.3.4. Probit Model_ Encounter Matched by Propensity Scores

An important advantage of using difference-in-differences method to cross-sectional estimators is that it allows controlling for time-invariant unobservable differences between the treatment and control group encounters (Heckman, Ichimura, & Todd, 1998; Caliendo, & Kopeinig, 2008). Propensity score refers to the conditional probability of participating in the proposed intervention which is the TCC intervention in our study. In this section we use the propensity scores for each encounter in the treatment group and identify its corresponding match in the control group based on encounters demographic characteristics and comorbidity composition.

To implement this model, the first step was to select a set of conditioning variables that are not directly influenced by the proposed intervention. Failure to do this will cause the matching estimator to not correctly estimate the effect of the intervention (Todd, 1999). We selected encounters' age and gender as well as their comorbidities because these characteristics of encounters are independent from implementation of TCC. The propensity score matching technique helps to reduce the dimension of the conditioning problem by estimating probabilities using a parametric procedure such as logit or probit model (Todd, 1999). Therefore, by using this method we can reduce matching on a one-dimensional estimate rather than identifying matches on multiple dimensions. We included a threshold control of 0.1 in our algorithm to ensure 90% match between the treatment encounters and control encounters. A threshold value is a value between zero and one where zero means an exact match. Therefore, smaller values produce closer matches. Our matching algorithm tries first for an exact match before trying for a propensity scored match.

Our data comprises of all encounters in two different hospitals in different regions. Therefore, we have a non-random sample of encounters. In order to rectify this problem, we have to provide a weighting of observations to obtain consistent estimates of propensity scores (Amemiya, 1985; Fan, 1993). We used log-odds ratio to estimate propensity scores matches of the encounters in the treatment group on an annual basis with the encounters in the control group. Table 10 shows our sample sizes on annual basis after matching encounters.

Table 10. Sample Sizes after Matching Encounters in Treatment and Control Groups

	Year						Total
	2009	2010	2011	2012	2013	2014	
Without TCC	248	292	371	346	400	135	1792
With TCC	248	292	371	346	400	135	1792
Total	496	584	742	692	800	270	3584

Table 11 presents the results of probit model for matched encounters between the treatment and control groups for all cause 30-day, 60-day and 90-day readmissions. The coefficients of the *treatment* after matching encounters is significant for both all cause 30-day and 60-day readmissions. This suggests that TCC implementation reduces all cause 30-day readmission by 4% even after controlling for demographics and comorbidities. In addition, this also suggests that although reduction in all cause 60 day readmissions is only 1% but this reduction is due to TCC implementation. The impact of TCC on all cause 90-day readmissions remains insignificant even after matching the encounters.

Table 11. Probit Results: All Cause Readmissions after Matching Encounters

Variables	**All Cause 30-Day Readmission**	**All Cause 60-Day Readmission**	**All Cause 90-Day Readmission**
Age	0.07 (0.05)	0.04 (0.09)	0 (0.08)
Gender	-0.05 (0.06)	0.21 (0.1) *	-0.18 (0.08) *
Congestive Heart Failure	-0.52 (0.09) *	0.01 (0.18)	-0.01 (0.15)
Renal Failure	-0.37 (0.08) *	-0.2 (0.14)	0.39 (0.1) *
Specified Heart Arrhythmias	-0.1 (0.08)	-0.17 (0.15)	-0.01 (0.12)
Cardio-Respiratory Failure and Shock	-0.07 (0.09)	0.03 (0.14)	-0.03 (0.12)

Variables	All Cause 30-Day Readmission	All Cause 60-Day Readmission	All Cause 90-Day Readmission
Diabetes	0.09 (0.09)	-0.06 (0.16)	-0.05 (0.15)
Chronic Obstructive Pulmonary Disease	-0.48 (0.12) *	0.13 (0.16)	0.14 (0.15)
Malnutrition and Obesity	-0.34 (0.16) *	0.19 (0.19)	0.26 (0.18)
Acute Myocardial Infarction	-0.71 (0.18) *	-0.55 (0.36)	0.24 (0.17)
Septicemia, Sepsis	-0.39 (0.16) *	0.16 (0.23)	-0.11 (0.23)
Cancer	-0.69 (0.26) *	-0.24 (0.4)	0.23 (0.25)
Vascular Diseases	-0.31 (0.19)	0.2 (0.26)	0.16 (0.24)
Ischemic Strokes	-0.73 (0.35) *	-3.75 (0.23)	0.29 (0.32)
Hematological and Immunity Disorders	0.07 (0.19)	-0.23 (0.4)	0.05 (0.27)
Head and Hip Fractures	-0.37 (0.26)	-3.73 (0.23)	0.06 (0.34)
Hemiplegia/Hemiparesis	0.3 (0.24)	-3.79 (0.23)	0.53 (0.29) *
Unstable Angina	-0.18 (0.23)	-0.07 (0.4)	0.16 (0.33)
Aspiration and Pneumonias	0.33 (0.2) *	-0.39 (0.19)	-0.36 (0.77)
Major Organ Transplant or Replacement	0.34 (0.26)	-0.39 (0.28)	0.38 (0.37)
Treatment (γ_0)	0.13 (0.08) *	0.23 (0.13) *	0.09 (0.12)
PostJan2012 (γ_1)	0.07 (0.08)	0.06 (0.14)	0.15 (0.12)
Treatment x PostJan2012 (γ_2)	-0.10 (0.11)	-0.15 (0.19)	-0.09 (0.16)
Pseudo R^2	0.17	0.15	0.14
TCC effect	-0.04	-0.01	-0.01

Similarly, we analyzed the probit results after matching encounters for heart failure readmissions. Table 12 presents the results of probit model for matched encounters between the treatment and control groups for heart failure 30-day, 60-day and 90-day readmissions. Interestingly in this case the reduction in both heart failure 30-day and 60-day are significant for the matched encounters. Our analysis shows that TCC implementation reduces both heart failure 30-day and 60-day readmissions by 6%. The impact of TCC on heart failure 90-day readmissions remains insignificant even after matching the encounters.

Table 12. Probit Results: Heart Failure Readmissions after Matching Encounters

Variables	HF 30-Day Readmission	HF 60-Day Readmission	HF 90-Day Readmission
Age	0 (0.08)	0.01 (0.14)	-0.12(0.12)
Gender	-0.07 (0.08)	0.31 (0.16) *	-0.08(0.13)
Congestive Heart Failure	4.18 (0.86)	3.9 (0.21)	4.27(0.21)
Renal Failure	-0.29 (0.13) *	-0.47 (0.27) *	0.37(0.14) *
Specified Heart Arrhythmias	-0.33 (0.13) *	-0.36 (0.27)	0.04(0.18)
Cardio-Respiratory Failure and Shock	-0.12 (0.13)	0.03 (0.2)	0.23(0.17)
Diabetes	-0.22 (0.15)	-0.12 (0.25)	-0.02(0.23)
Chronic Obstructive Pulmonary Disease	-0.38 (0.19) *	0.35 (0.2) *	-0.36(0.29)
Malnutrition and Obesity	-0.74 (0.37) *	-0.31 (0.4)	0.25(0.26)
Acute Myocardial Infarction	-0.49 (0.27) *	-4.23 (0.27)	-4(0.29)
Septicemia, Sepsis	-0.65 (0.36) *	0.04 (0.4)	-3.99(0.31)
Cancer	-0.59 (0.39)	0.12 (0.42)	0.27(0.32)
Vascular Diseases	-0.18 (0.28)	-3.89 (0.40)	0.29(0.31)
Ischemic Strokes	-4.29 (0.24)	-3.67 (0.58)	-4.46(0.57)
Hematological and Immunity Disorders	0.32 (0.23)	0.13 (0.42)	0.33(0.33)
Head and Hip Fractures	-4.25 (0.22)	-3.79 (0.55)	-4.15(0.56)
Hemiplegia/Hemiparesis	0.29 (0.39)	-3.92 (0.54)	0.9(0.39) *
Unstable Angina	0.08 (0.31)	-3.93 (0.54)	-3.88(0.55)
Aspiration and Pneumonias	-0.27 (0.43)	-4.01 (0.47)	-4(0.47)
Major Organ Transplant or Replacement	0.19 (0.48)	-4.37 (0.61)	-3.74(0.68)
Treatment (γ_0)	-0.13 (0.11)	0.35 (0.2) *	0.14(0.18)
PostJan2012 (γ_1)	-0.07 (0.12)	0.02 (0.22)	-0.01(0.19)
Treatment x PostJan2012 (γ_2)	-0.08 (0.16)*	-0.3 (0.29)*	0.03(0.25)
Pseudo R^2	0.17	0.12	0.09
TCC effect	-0.06	-0.06	0.00

Table 13 presents the results of probit model with matched encounters for other cost and quality of care measures such as inpatient length of stay, cost of all services provided during an encounter as well as ER visits for patients with a history of heart failure. The *treatment* coefficient (γ_0) remains significant for length of stay even after matching encounters. We do not observe significant changes in the interaction effect (γ_2). The overall TCC effect on encounters length of stay remains significant even after matching encounters and shows that TCC implementation reduces average length of stay by 2%.

In terms of total charges, we can see little changes in time coefficient (γ_1). But it still remains significant after matching encounters. This suggests that for a similar encounter the cost of care is slightly higher after 2012. We do not observe significant differences in the overall TCC impact of the cost of services after matching encounters.

The results of the probit model on ER visits are very interesting after matching encounters. These coefficients are presented in the third column of table 13. We observe differences in all three coefficients of *treatment* (γ_0), *PostJan2012* (γ_1) and the interaction term (γ_2). This once again suggests that encounters comorbidities and demographic composition between the treatment and control group have significant impact on patients returning to ER after discharge from inpatient setting. The overall TCC effect on encounters ER visits is significant after matching encounters. Our analysis shows that TCC implementation reduces ER visits by 4%.

Table 13. Probit Results: Length of Stay, Costs and ER Visits after Matching Encounters

Variables	**Length of Stay**	**Total Charges**	**ER visits**
Age	-0.02 (0.04)	-0.07 (0.05)	0 (0)
Gender	0.08 (0.04) *	-0.01 (0.05)	-0.02 (0.04)
Congestive Heart Failure	0.26 (0.08) *	0.19 (0.09) *	-0.07 (0.06)
Renal Failure	0.26 (0.06) *	0.43 (0.06) *	-0.03 (0.12)
Specified Heart Arrhythmias	0.04 (0.06)	0.27 (0.07) *	0 (0.08)
Cardio-Respiratory Failure and Shock	0.28 (0.06) *	0.52 (0.07) *	-0.02 (0.13)
Diabetes	-0.12 (0.07) *	-0.39 (0.09) *	-0.05 (0.05)
Chronic Obstructive Pulmonary Disease	-0.2 (0.08) *	-0.21 (0.09) *	0.11 (0.11)
Malnutrition and Obesity	0.04 (0.11)	0.05 (0.11)	-0.05 (0.21)
Acute Myocardial Infarction	0.09 (0.1)	0.91 (0.11) *	-0.24 (0.34)
Septicemia, Sepsis	0.55 (0.12) *	0.7 (0.12) *	-0.3 (0.37)
Cancer	0.2 (0.15)	0.3 (0.15) *	-0.15 (0.24)
Vascular Diseases	0.22 (0.14)	0.31 (0.15) *	0.22 (0.25)
Ischemic Strokes	0.01 (0.21)	0.54 (0.22) *	0.21 (0.32)
Hematological and Immunity Disorders	-0.18 (0.15)	0.13 (0.16)	-0.48 (0.32)
Head and Hip Fractures	0.53 (0.2) *	0.79 (0.2) *	-0.09 (0.27)
Hemiplegia/Hemiparesis	0.36 (0.21) *	-0.27 (0.24)	0 (0)
Unstable Angina	-0.37 (0.19) *	0.26 (0.2)	-0.21 (0.16)
Aspiration and Pneumonias	0.57 (0.19) *	0.66 (0.18) *	1.96 (0.64) *
Major Organ Transplant or Replacement	0.22 (0.25)	0.4 (0.25)	0.06 (0.25)
Treatment (γ_0)	0.13 (0.06) *	0.11 (0.07)	0.01 (0.06) *
PostJan2012 (γ_1)	-0.01 (0.06)	0.19 (0.07) *	-0.13 (0.06) *
Treatment x PostJan2012 (γ_2)	0.04 (0.09)	-0.04 (0.09)	-0.04 (0.09) *
Pseudo R^2	0.14	0.11	0.16
TCC effect	-0.02	-0.01	-0.04

Table 13a. Hypothesis Testing of Probit Results: HF Patients with TCC vs. without TCC after Matching Encounters

Hypothesis 1	The transitional care clinic has a significant effect on reducing 30-Day Heart-Failure Readmissions in the treatment group. (significant within group difference)	Supported
Hypothesis 2	The transitional care clinic has a significant effect on reducing 30-Day Heart-Failure Readmissions between the treatment and control group. (significant between group difference)	Supported
Hypothesis 3	The transitional care clinic has a significant effect on reducing 60-Day Heart-Failure Readmissions in the treatment group. (significant within group difference)	Supported
Hypothesis 4	The transitional care clinic has a significant effect on reducing 60-Day Heart-Failure Readmissions between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 5	The transitional care clinic has a significant effect on reducing 90-Day Heart-Failure Readmissions in the treatment group. (significant within group difference)	Not Supported
Hypothesis 6	The transitional care clinic has a significant effect on reducing 90-Day Heart-Failure Readmissions between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 7	The transitional care clinic has a significant effect on reducing 30-Day All Cause Readmissions in the treatment group. (significant within group difference)	Supported
Hypothesis 8	The transitional care clinic has a significant effect on reducing 30-Day All Cause Readmissions between the treatment and control group. (significant between group difference)	Supported
Hypothesis 9	The transitional care clinic has a significant effect on reducing 60-Day All Cause Readmissions in the treatment group. (significant within group difference)	Not Supported
Hypothesis 10	The transitional care clinic has a significant effect on reducing 60-Day All Cause Readmissions between the treatment and control group. (significant between group difference)	Not Supported

Hypothesis 11	The transitional care clinic has a significant effect on reducing 90-Day All Cause Readmissions in the treatment group. (significant within group difference)	Not Supported
Hypothesis 12	The transitional care clinic has a significant effect on reducing 90-Day All Cause Readmissions between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 13	The transitional care clinic has a significant effect on reducing length of stay in the treatment group. (significant within group difference)	Not Supported
Hypothesis 14	The transitional care clinic has a significant effect on reducing length of stay between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 15	The transitional care clinic has a significant effect on reducing total cost of care in the treatment group. (significant within group difference)	Not Supported
Hypothesis 16	The transitional care clinic has a significant effect on reducing total cost of care between the treatment and control group. (significant between group difference)	Not Supported
Hypothesis 17	The transitional care clinic has a significant effect on reducing ER visits for patients with previous inpatient encounters in the treatment group. (significant within group difference)	Supported
Hypothesis 18	The transitional care clinic has a significant effect on reducing ER visits for patients with previous inpatient encounters between the treatment and control group. (significant between group difference)	Supported

4.4. Cluster Analysis: Considering Patient Heterogeneity

Helm et al (2015) note that many studies on the cost and quality of care rely on a siloed approach. They do not effectively consider heterogeneity in the demographic, socio-economic or clinical characteristics. This creates difficulty in generalizability as well as in the ability to specifically apply results. Patients with different disease conditions have different needs. Their patient flows, including the clinical and administrative workflows are directly impacted by comorbidities. Anecdotally, care providers and administrative managers recognize their different needs and impact on the patient flow, particularly for TCC. However, little in the literature informs management in planning interventions that improve patient flow while considering heterogeneity in patients' conditions. We use cluster analysis techniques to breach this gap and identify the impact of TCC on patients with different comorbidity compositions. The results of our probit analysis also revealed that there are significant differences between encounters with different comorbidity compositions in terms of our outcome measures of cost and quality of care.

Cluster analysis partitions the data into meaningful subgroups. In cluster analysis we search for patterns in hospital encounters by grouping observations into clusters. Our objective is to maximize the similarity of encounters within a cluster while making sure that the clusters are dissimilar (Kaufman and Rousseeuw, 1990; Fraley and Raftery, 1998). Clustering methods usually follow either a hierarchical strategy or adopt relocation techniques. Hierarchical methods proceed by stages producing a sequence of partitions, each corresponding to a different number of clusters. Relocation methods move observations iteratively from one group to another, starting from an initial partition (Fraley and Raftery, 1998). For clustering via mixture models, relocation techniques are usually based on the Expectation Maximization (EM) algorithm (Dempster, Laird, & Rubin, 1977). Partitions are determined by a combination of hierarchical clustering and the expectation-maximization (EM) algorithm for maximum likelihood. Several studies identified that this approach provide better performance than other clustering methods (eg. Fraley and Raftery, 1998; Halkidi, Batistakis, & Vazirgiannis, 2001).

We conducted both hierarchical cluster analysis using Ward's method as well as EM algorithm to identify optimal clusters of encounters. We included encounter's comorbidities, the severity of their disease as well as their history of readmission to hospital in our cluster analysis. Both EM algorithm and Ward's method divided data into two meaningful clusters. The first cluster includes encounters with multiple comorbidities and represent the more complex patients. We refer to encounters in this cluster as complex patients. The second cluster is comprised of encounters that are solely suffer from heart failure. Therefore, we refer to encounters in this cluster as heart failure patients. We test the impact of TCC on cost and quality of care outcome measures and compare the trends of variations for each cluster.

Figure 12 shows the impact of TCC on all cause 30-day readmissions for encounters in our two clusters: complex patients and heart failure patients. The results of probit model shows that TCC significantly reduce all cause 30-day readmissions for complex patients. We also observe that the although hospital with TCC managed to control the all cause 30 day readmissions compare to the hospital without TCC for heart failure patient, the difference in changes is not significant. We do not observe any significant impact of TCC across cluster on all cause 60-day and 90-day readmission.

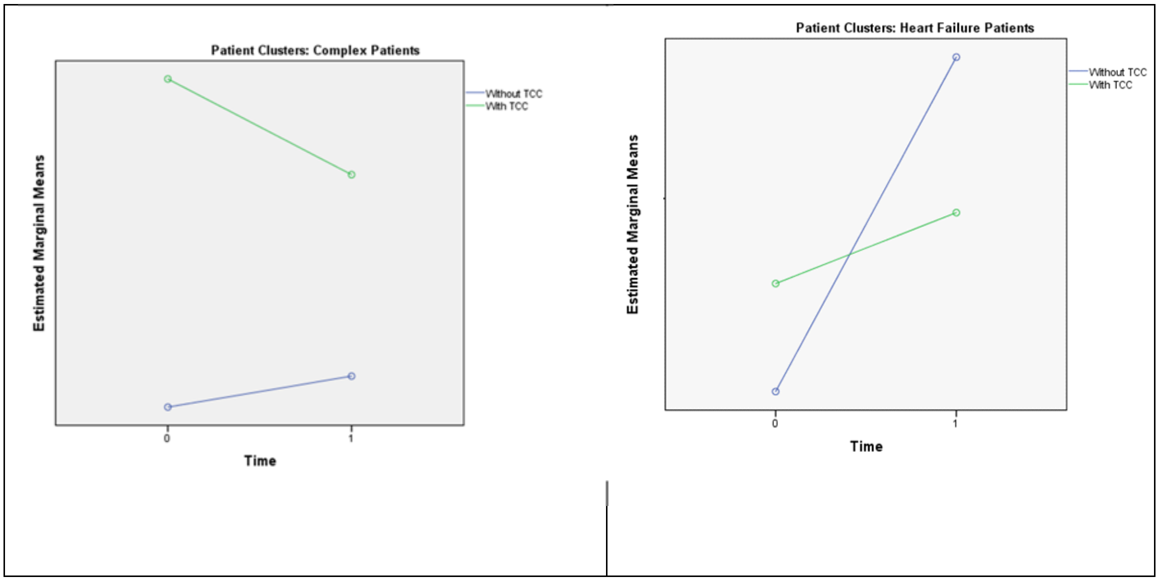


Figure 12. TCC Impact on All Cause 30-Day Readmission_ Complex vs HF Patients

The impact of TCC on heart failure 30-day and 60-day readmissions for complex patients versus heart failure patients are presented in figure 13 and 14 respectively. The results of probit model shows that TCC significantly reduce HF 30-day and HF 60-day readmissions for complex patients. But we do not observe a significant difference in the trends of readmission for HF patients. This analysis tests our hypotheses presented in tables 3a and 6a in the complex patients and heart failure patients' clusters.

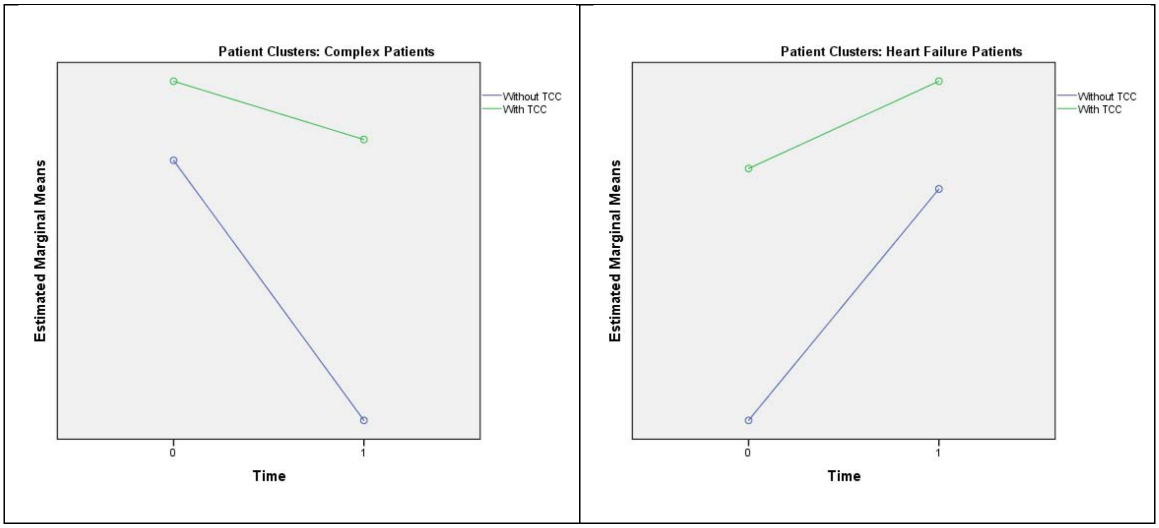


Figure 13. TCC Impact on HF 30-Day Readmission_ Complex vs HF Patients

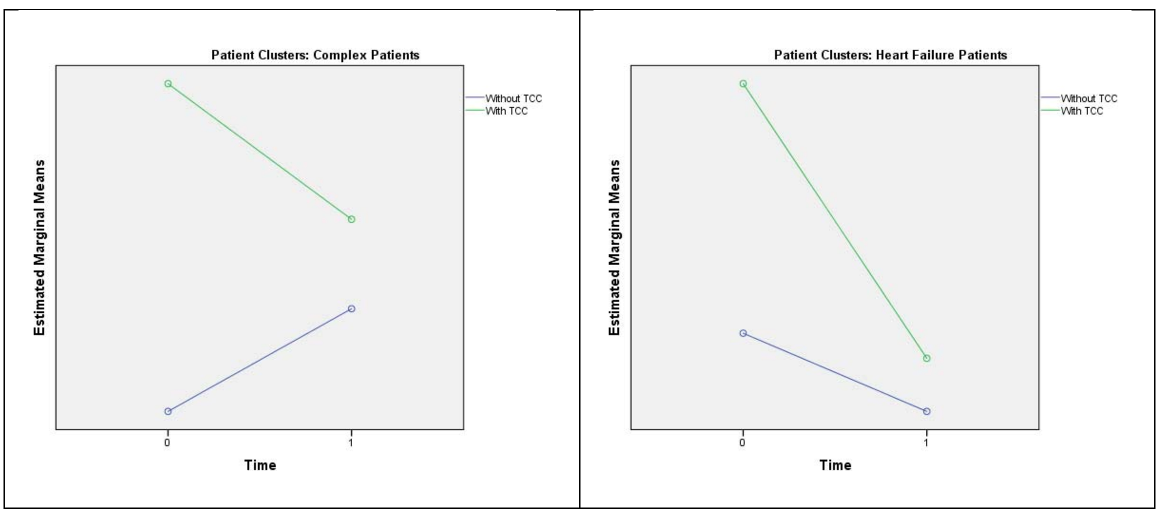


Figure 14. TCC Impact on HF 60-Day Readmission_ Complex vs HF Patients

The results of our analysis shows that TCC has more impact on reducing the ER visits for more complex patients.

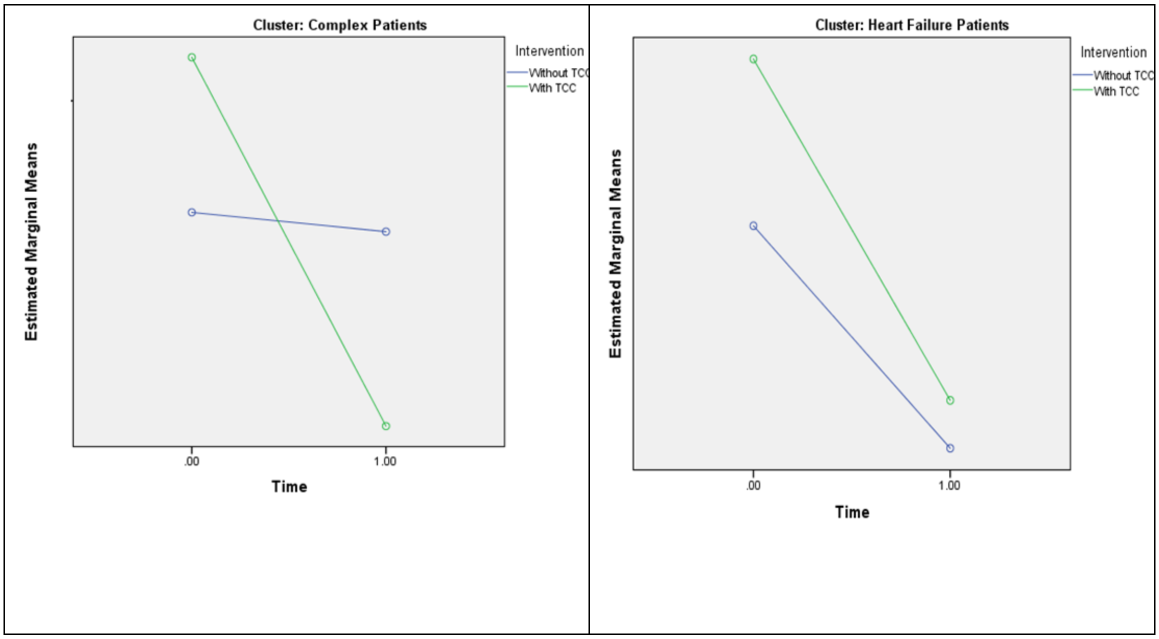


Figure 15. TCC Impact on ER Visits_ Complex vs HF Patients

4.5. Cluster Analysis: Patients with Specific Comorbidities

We conduct hierarchical clustering analysis to understand clusters of comorbidities specific to patients with heart failure. We identify four clusters each representing patients with high impact disease conditions including COPD, renal failure, diabetes and patients with sepsis, pneumonia and other conditions. We conduct multivariate analysis to compare each outcome variable before and after the implementation of the transitional care interventions for each cluster. Figures 6 through 8 show our results for each cluster. Estimated marginal means of Length of Stay for patient clusters of comorbidities are shown in figure 16. There are significant differences in average length of stay between patients with diabetes, renal failure and pneumonia.

Implementing TCC significantly reduced length of stay in hospital for patients with these co-morbidities.

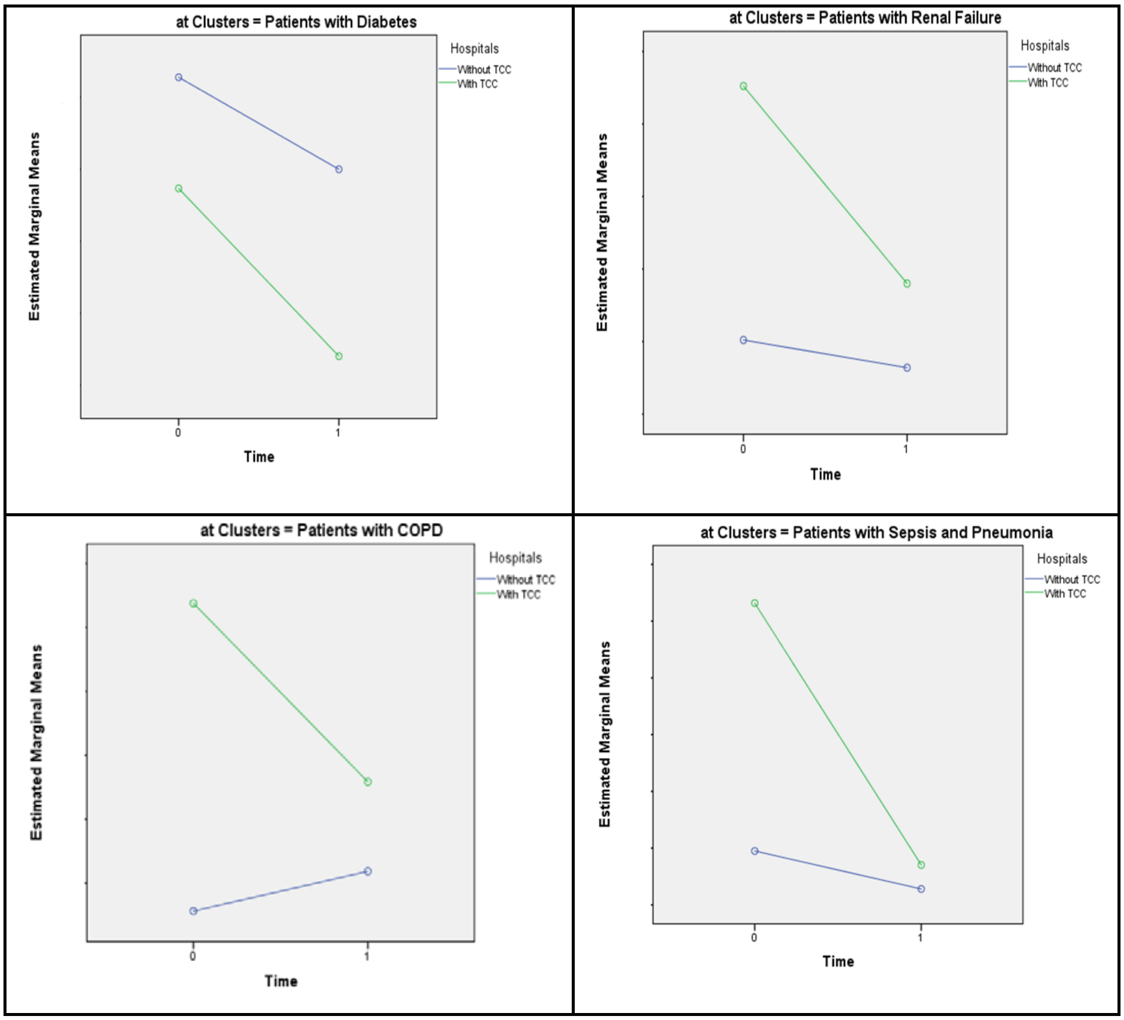


Figure 16. Estimated Marginal Means of Length of Stay for Patient Clusters of Comorbidities

The estimated marginal means of the number of days before readmission for patient clusters of comorbidities are shown in figure 17. The results of mean comparison between clusters shows that TCC intervention significantly increase the number of days to readmission for patients with diabetes and Sepsis.

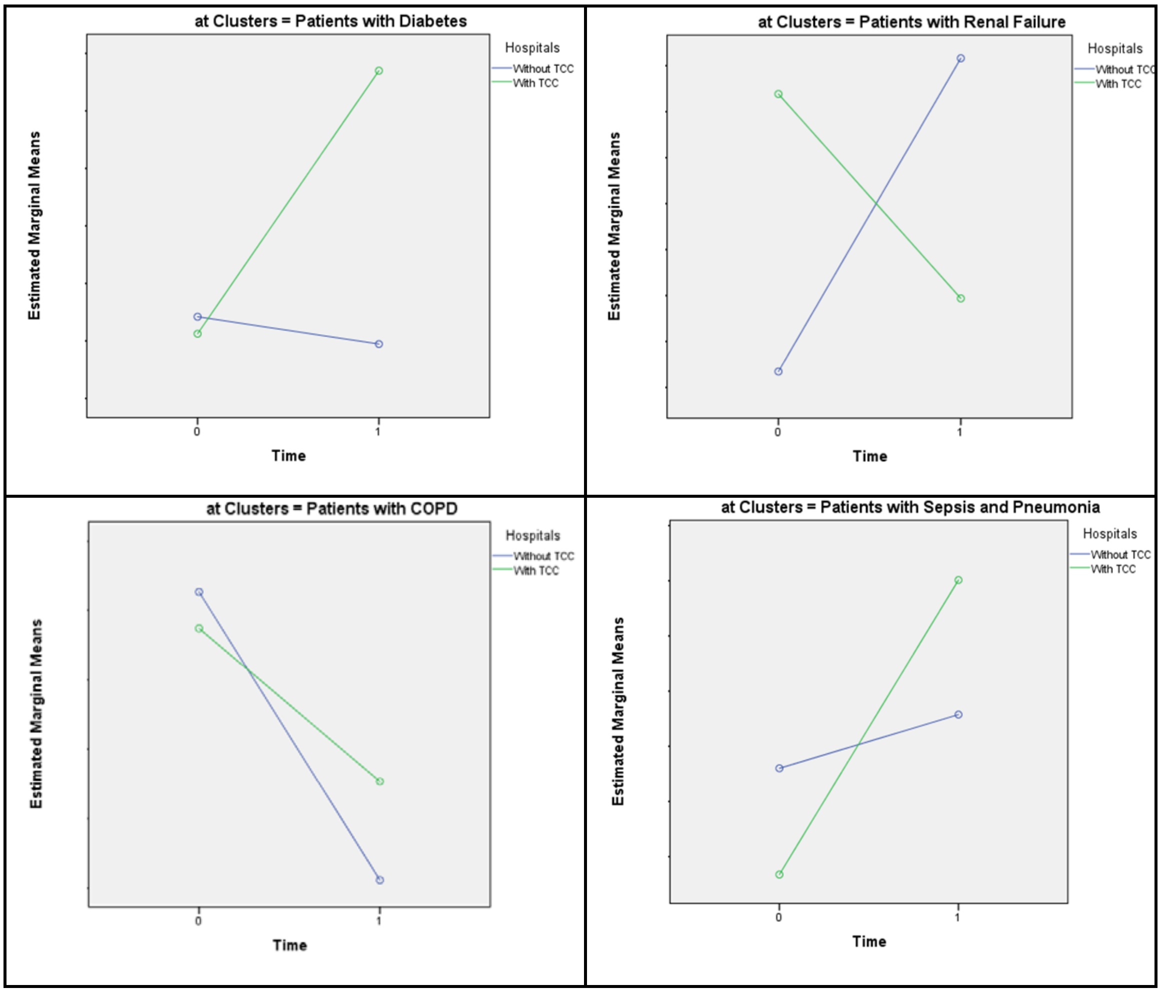


Figure 17. Estimated Marginal Means of Time to Readmission for Patient Clusters of Comorbidities

The estimated marginal means of the total costs of care for patient clusters of comorbidities are shown in figure 18. There are significant differences in average cost of care between patients with different comorbidities. Patients with renal failure face significantly higher costs compare to patients with diabetes and pneumonia. Implementation of TCC significantly reduce costs of care for patients with COPD.

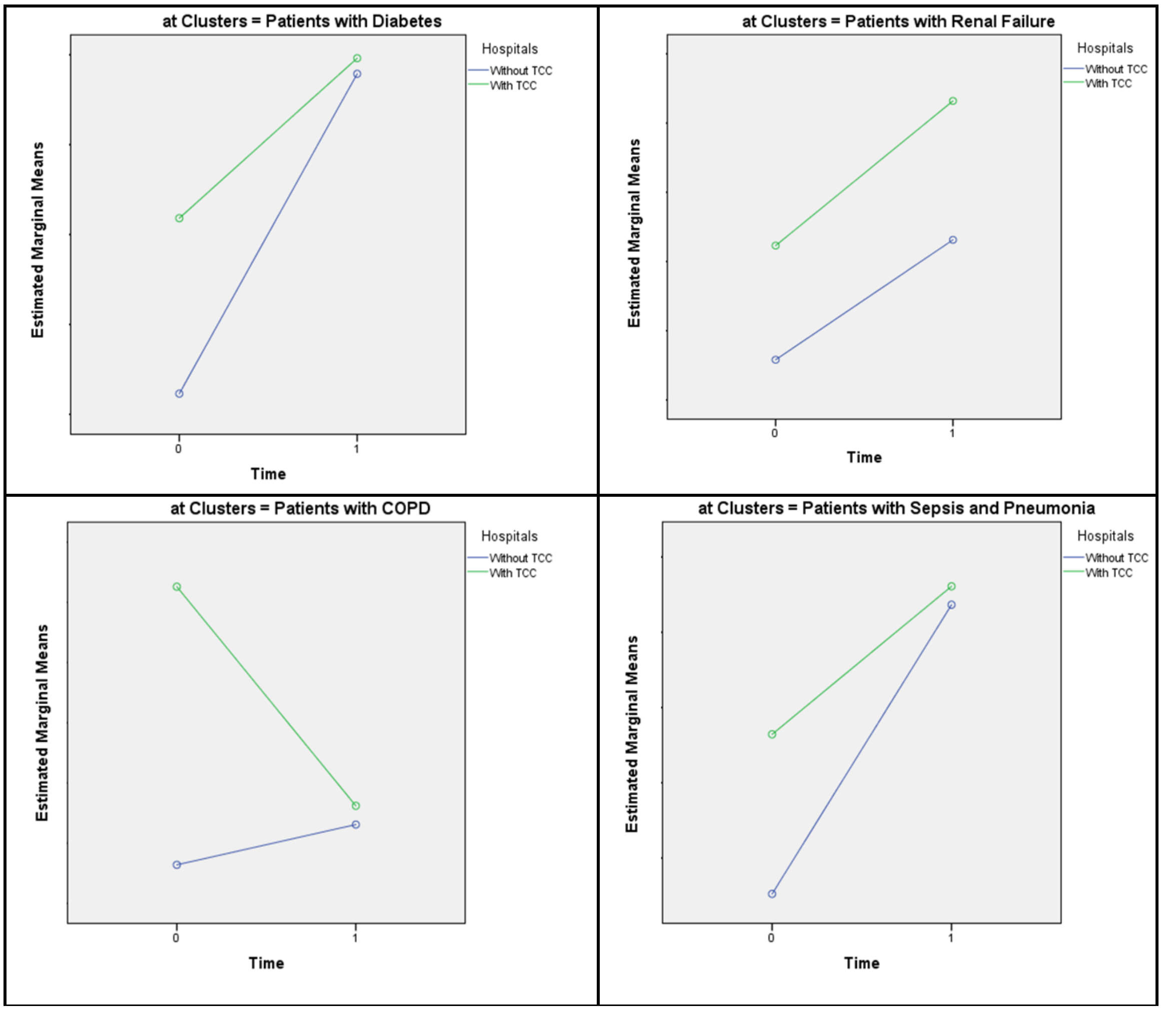


Figure 18. Estimated Marginal Means of Total Charges for Patient Clusters of Comorbidities

The estimated marginal means of the number of emergency department visits for patient clusters of comorbidities are shown in figure 19. The results of mean comparison between clusters shows that TCC intervention significantly decrease number of ED visit for patients with COPD, sepsis and pneumonia.

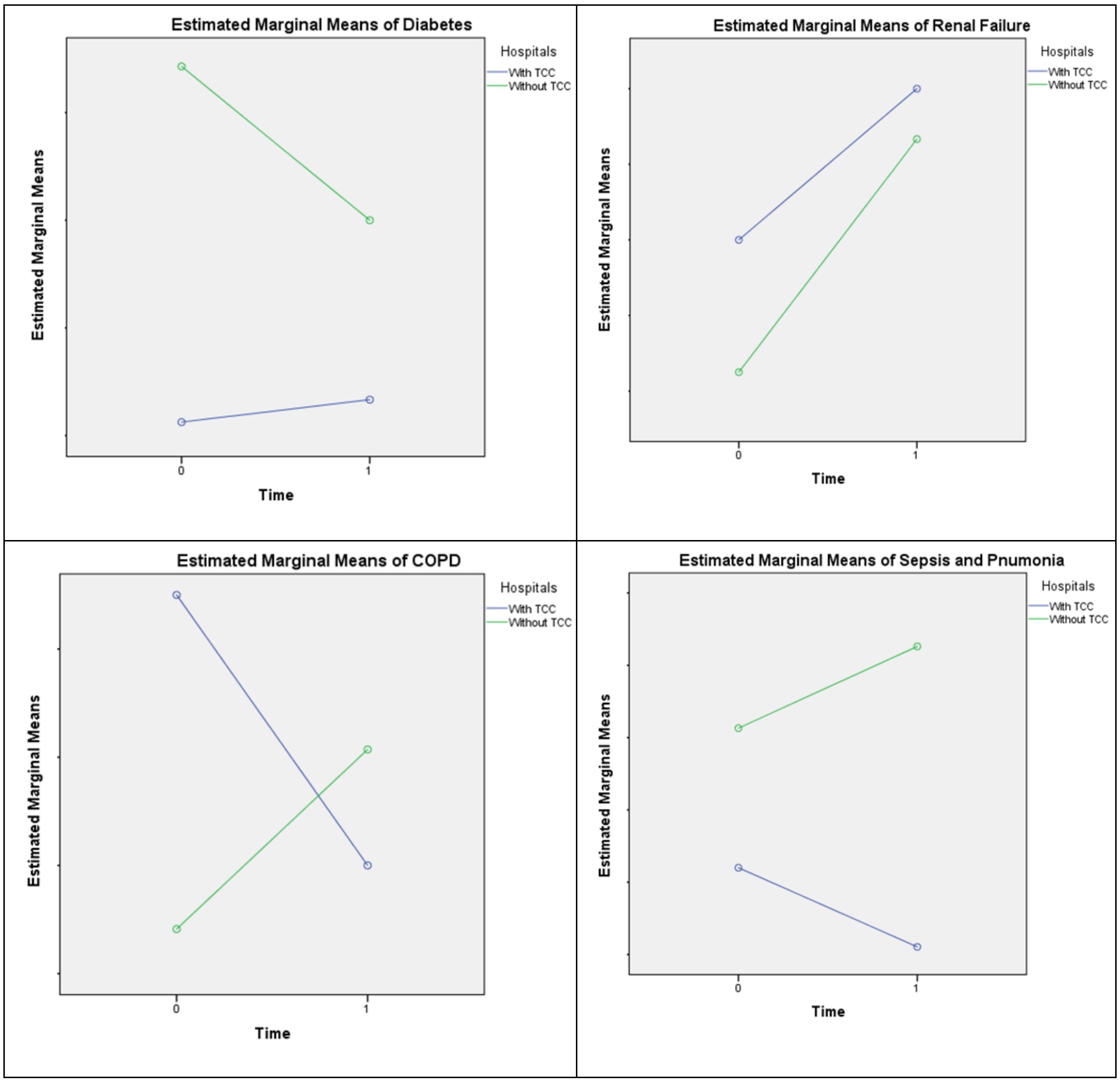


Figure 19. Estimated Marginal Means of Emergency Department Visits for Patient Clusters of Comorbidities

4.6. Conclusion

We investigate the efficacy of the transition care clinic as an intervention for patients with heart failure and study the impact of this intervention on the cost and quality of care. We show that hospitals can effectively manage the inflow and the outflow of patients with heart failure through mechanisms such as transition care clinics that can provide a robust way of coordinating care. We account for heterogeneity in HF patients' population and compare the impact of TCC on complex patients who have multiple comorbidities with patients who only have heart failure. Further we investigate the impact of TCC for patients with different comorbidities such as renal failure, diabetes, COPD, sepsis and pneumonia. This study contributes to the design of patient flow management activities that can be implemented at transition care clinics for HF patients with different comorbidities. Healthcare presents an opportunity for researchers and practitioners to develop innovative policies and investigate their impact in their own natural setting. our use of natural experiments can spur other researchers' interest to adopt and further develop the utility of this, seldom used, methodology in operations management and healthcare research.

CHAPTER V

ESSAY 3_ SELF-CARE MANAGEMENT FOR PATIENTS WITH HEART FAILURE

5.1. Introduction

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). 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 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 develop an assessment instrument which is the main artifact of a mHealth tool for patients with heart failure to be able to assess their health and psychological condition and be more engaged in their self-care. The motivating hypothesis of this study is that with appropriately validated intelligence and assessment, mHealth systems can be designed to inform, and improve and guide self-care activities of patients. This, in turn, helps them engage in effective self-care and achieve the self-confidence necessary.

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. Heart failure is a chronic disease. It requires consistent monitoring of patients' health conditions and clinical symptoms, such as shortness of breath and abrupt weigh 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 et. al., 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.

We propose that for patients with heart failure, effective self-care behaviors and awareness of their conditions can be improved by using mHealth tools. These in turn, 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 that collect data and provide information to both the patient as well as their care providers. This will increase the quality of care and reduce costs for the provider. Moreover, we propose that 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 key cost and quality measures such as fewer readmissions. The study is motivated to develop and employ effective analytics that are the key intelligence components in the design of such interventions. In this essay, we develop an assessment tool for patients with heart failure to understand their conditions better and be more involved in the management of their health conditions. This assessment tool is the necessary foundation without which effective mHealth interventions such as those described here cannot be scientifically designed and develop. This tool measures patients' health condition and informs their decisions, based on their scores, to avoid unnecessary readmissions and ER visits.

5.2. Background and Theoretical Framework

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 t*o live successfully with CHF, it is important to develop confidence*. This confidence includes self-assurance, positive and healthy actions and expectations that desirable health outcomes can be achieved. This confidence can be achieved taking self-care in managing the HF, including a level of understanding about the medical condition, knowing what symptoms to monitor and making informed decisions to minimize symptoms and respond effectively to symptoms.

The clinical literature provides multiple well-established studies to guide the development of educational materials and self-care mechanisms for patients with heart failure. 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. Riegel et al (2004) 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 for 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, Calvilo-King et al (2012) find that a broad range of social factors impact risks for the HF patient. They call for more research on identification of such factors and their impact on patients and care providers.

Riegel et al (2009) define 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. (Riegel, et al, 2009). We utilized these and investigate the addition of patient engagement and self-efficacy to develop a more cohesive instrument to be delivered as mHealth tool for patients with heart failure. We propose that mHealth initiatives 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.

5.3. Research Approach

This study will be implemented in five stages as shown in figure 1 below and described in further detail in the sections that follow. The item pool was constructed by a panel of experts and health providers who interact with patients with heart failure every day. The items are also validated by the administrative and quality management team members. We use two-parametric logistic model (2PL) as well as the Rasch Partial Credit Model to analyze the items. Our process to assess the reliability and validity of the domains for measurement development is described in figure 20.

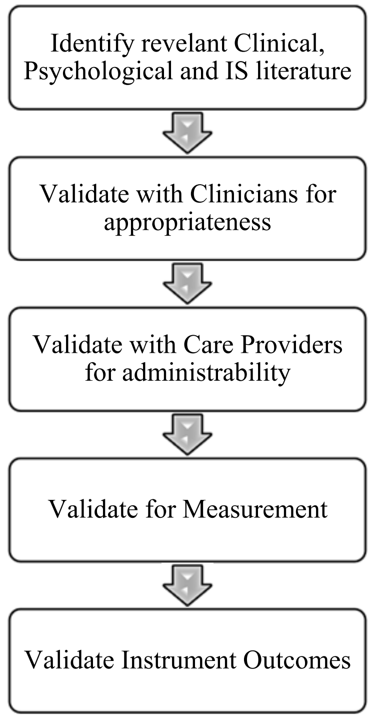


Figure 20. Developing an Analytics-Based m-Health System for Improved Self-Care of Heart Failure Patients

5.4. Instrument Development

Review of published literature that discuss the self-care process for chronic diseases include self-care management, self-care maintenance (eg. Reigel, et al, 2015), confidence and engagement (eg. Hibbard, Stockard, Mahoney, & Tusler, 2004). Better health outcomes are linked to higher level of engagement (Von Korff et. al., 1997; Bodenheimer et al., 2002) and better self-care maintenance and management (Jaarsma et al., 2003; Artinian et al., 2002). Literature also shows that there is a positive relationship between patients' ability and awareness of preventive actions and their health outcomes. Hibbard et al., (2004) indicate that the ability of patients to manage their symptoms as well as their level of engagement in activities to maintain their health condition are more likely to have better health outcomes. Based on our review of literature for patients with heart failure we propose that both patients' self-care behavior as well as patients' engagement are drivers of improved health outcomes and contributes to lower readmission rates and ER visits. We use these propositions to develop mHealth assessment tool for patients with heart failure.

We proceed item development for heart failure assessment instrument through an expert consensus process. The panel of experts included two cardiologists, two heart failure physician assistants, two nurses and three members of care management team. The process involved multiple round table meetings. The first round of meetings was designed to elicit the broad range of ideas about the domains to be included. We began with the domains developed from our literature review such as symptom recognition, symptom management and confidence in health education derived from current heart failure assessment tools. We also included patient activation, self-efficacy and self-determination from chronic disease assessment literature. The experts discussed and rated the importance of each domain. The results of these discussions revealed considerable consensus among experts. They suggest that three domains should be included in the assessment. These are symptom recognition, health management and patient engagement.

Based on the results from the expert panel we derive conceptual definitions for the three main domains. Symptom recognition refers to patients understanding of heart failure symptoms such as shortness of breath and swelling. Health management refers to self-care behaviors and actions that patients with heart failure have to follow in order to maintain their health condition. These actions involve healthy eating and weight management as well as compliance with their prescribed medications. Patient engagement refers to patients' level of confidence in their knowledge about their health condition and treatments as well as their social engagement and behavior. We used these definitions as the basis for developing the measures and writing items. The experts developed an item pool 25 items. The items were developed based on the domain that they were supposed to measure and reviewed for content and face validity. After thorough revisions by the experts, number of items reduced to 19.

5.5. Pilot Study

The instrument was tested in a pooled convenience sample of 100 patients with heart failure. Some patients completed the instrument themselves in the heart failure clinic, while others were assisted and interviewed by a nurse. We collected patients' responses both electronically on a tablet as well as on paper. We calculated patients' scores on each domain as well as the overall assessment score. Table 14 shows patients' scores on each domain and their overall score.

Table 14. Descriptive Statistics of Patients' Domain Scores (n=100)

Domain	**Mean**	**Std. Dev.**
Symptom Recognition	75.7	9.4
Health Management	68.8	24.8
Patient Engagement	70.4	2.1
Heart Failure Overall Index	72.8	12.5

Overall, symptom recognition was high. 75% of the patients in this sample claim that they can identify their symptoms. Health management scores were relatively low compared to other domains. A majority of the respondents do not exercise as they should.

5.5.1. Item Analysis Using Two-Parameter Logistic Model

The initial set of items were selected using two-parameter logistic (2PL) model that estimates two parameters: difficulty and discrimination. Item difficulty (b) is a location index that describes item location along the ability scale (De Ayala, 2013). Item discrimination (a) refers to how well an item separates respondents on the left side of the item location from those with to the right of the item location. Table 15 shows item difficulty and item discrimination estimates for heart failure assessment. The discrimination parameter estimates (a) vary between 0.09 and 2.53. The corresponding standard errors vary from 0.25 to 3.23. We expect to see such a large range because the sample size of the pilot study is relatively small (n=100).

Table 15. 2PL Model Item Parameter Estimates, Logit: *aθ* + *c* or *a*(*θ* – *b*)

Item	Label	*a*	*s.e.*	*c*	*s.e.*	*b*	*s.e.*
1	Q1	0.09	0.25	0.52	0.21	-5.86	16.54
2	Q2	1.43	0.69	3.09	0.78	-2.17	0.96
3	Q3	0.79	0.32	-0.39	0.31	0.49	0.40
4	Q4	0.99	0.42	1.87	0.47	-1.89	0.82
5	Q5	0.23	0.26	0.48	0.22	-2.14	2.55
6	Q6	1.46	0.55	2.25	0.71	-1.54	0.66
7	Q7	0.95	0.37	1.14	0.39	-1.20	0.58
8	Q9	1.02	0.50	2.63	0.66	-2.57	1.07
9	Q10	1.26	0.43	0.93	0.52	-0.74	0.49
10	Q11	2.41	2.21	6.09	4.55	-2.53	0.75
11	Q12	2.53	1.27	2.24	0.88	-0.89	0.54
12	Q13	0.85	0.36	1.05	0.31	-1.23	0.55
13	Q14	0.80	0.35	1.21	0.31	-1.51	0.69
14	Q15	2.37	1.08	2.04	0.89	-0.86	0.54
15	Q16	1.43	0.62	1.61	0.87	-1.13	0.37
16	Q8H	2.14	3.23	4.21	4.70	-1.97	0.84
17	Q8A	1.42	0.97	2.12	1.11	-1.49	0.40

Item	Label	*a*	*s.e.*	*c*	*s.e.*	*b*	*s.e.*
18	Q8F	1.03	0.77	1.89	0.76	-1.83	0.77
19	Q8S	1.16	0.74	2.25	0.85	-1.94	0.68

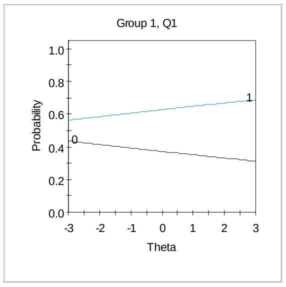
Table 16 presents item level chi-squared statistics and corresponding degrees of freedom to asses lack of fit for each item. Significant p-values represent lack of fit. The statistics tabulated for 2PL model shows that only item 8 which refers to swelling around ankles is significant at p=0.05 level. Chi-squared statistic for Q11 is not calculated because there was not enough variability in responses.

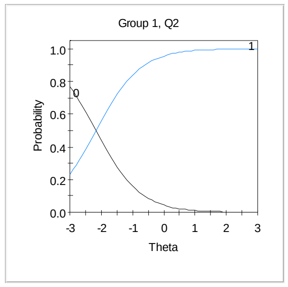
Table 16. S-X^2 Item Level Diagnostic Statistics

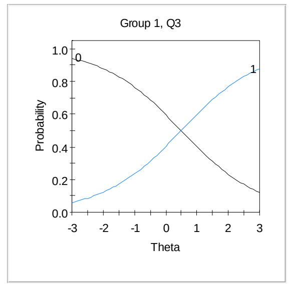
Item	Label	X^2	*d.f.*	Probability
1	Q1	12.18	9	0.2027
2	Q2	1.43	4	0.8393
3	Q3	4.30	7	0.7454
4	Q4	11.11	7	0.1335
5	Q5	11.29	8	0.1854
6	Q6	6.90	7	0.4412
7	Q7	4.45	8	0.8147
8	Q9	3.90	5	0.5649

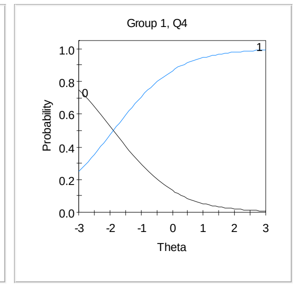
Item	Label	X^2	*d.f.*	Probability
9	Q10	7.15	7	0.4149
11	Q12	7.20	6	0.3046
12	Q13	10.92	7	0.1418
13	Q14	8.86	7	0.2648
14	Q15	5.81	5	0.3266
15	Q16	5.90	7	0.5524
16	Q8H	1.84	2	0.3994
17	Q8A	14.29	7	0.0461
18	Q8F	8.79	7	0.2700
19	Q8S	7.51	7	0.3788

We investigated the trace lines for each item. The trace lines for all items are presented in figure 21. Trace lines show the probability of impulsive responses for each item as a function of its underlying latent variable. We can observe that the slope of responses for item number 1 which refers to weight management and item number 5 which refers to eating management of the patients are low and responses change very little across all levels. Therefore, these two items provide very little information.


Group 1, Q1
Probability
Theta


Group 1, Q2
Probability
Theta


Group 1, Q3
Probability
Theta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Probability
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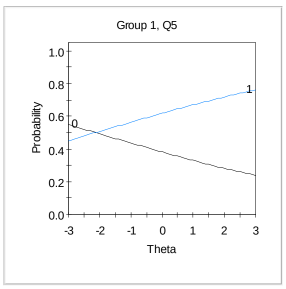
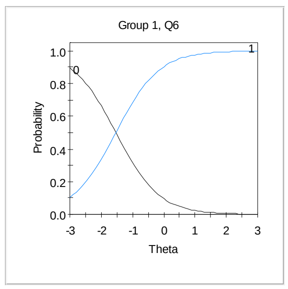

Group 1, Q5
Probability
Theta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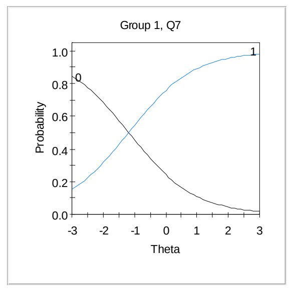
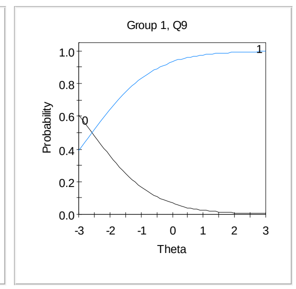
Probability
Theta


Group 1, Q7
Probability
Theta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Probability
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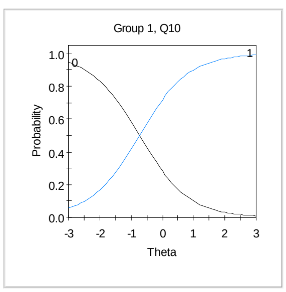
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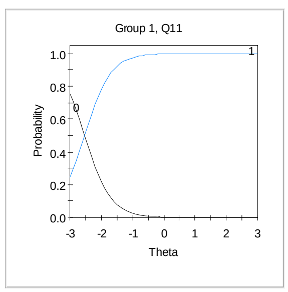
Probability
Theta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Probability
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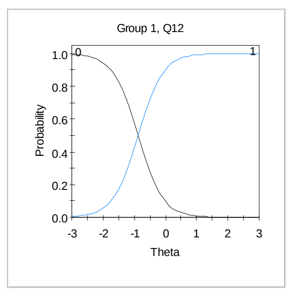
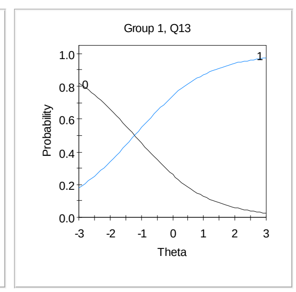
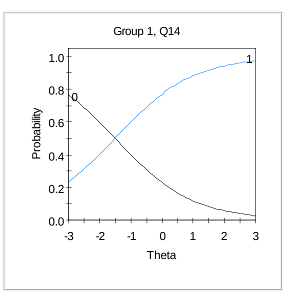
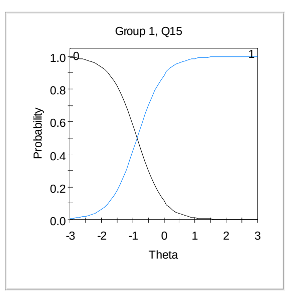
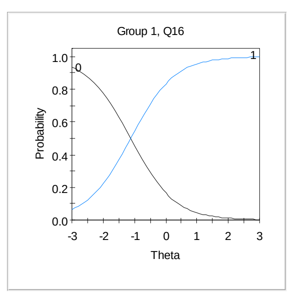
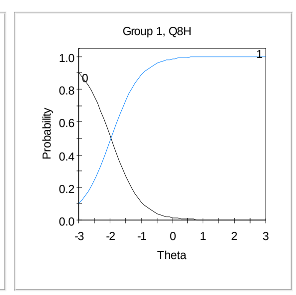

Group 1, Q12
Probability
Theta


Group 1, Q13
Probability
Theta


Group 1, Q14
Probability
Theta


Group 1, Q15
Probability
Theta


Group 1, Q16
Probability
Theta


Group 1, Q8H
Probability
Theta

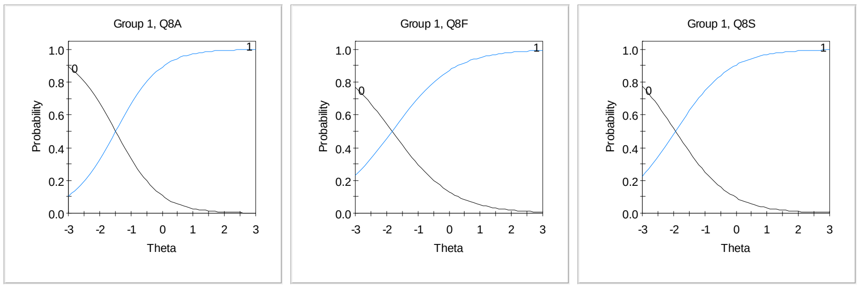


Figure 21. Item Trace Lines _ 2PL Model

5.5.2. Rasch Partial Credit Model

We used Rasch model for item analysis. Rasch measurement calibrates the difficulty of items in terms of response probability. Therefore, in order to endorse an item, we have to identify response distribution on the measure scale. Items in heart failure assessment developed using a 3-point Likert scale in which 1 represents no changes in patients' health condition and 3 represents a deterioration of patients' health. Using partial credit model allow us to use different thresholds for different items and helps us to understand the distribution of each response category for each item.

Item fit statistics using partial credit model are shown in table 17. In this case item selection is based on deviation of the item from model's expectations. Smith (1996) provides descriptions of fit criteria. Fit values greater than 2.0 refer to more stochastic variability in responses than expected and distort the measurement system. Fit value between 1.5 and 2 are not productive for measurement construction but at the same time they are not degrading it. Fit values between 0.5 and 1.5 are productive for measurement development where a value of 1.0 represent perfect fit. Values less than 0.5 may produce misleadingly good reliabilities and separations.

We calculated two item fit statistics: Infit and Outfit. Infit is an information-weighted residual and is most sensitive to item fit when the item's scale location is close to the respondent's scale location. Outfit is more sensitive to item fit for items with a scale location that is distant from the respondent's scale location.

Table 17. Preliminary Item Analysis with Calibration

Item	Calibration	SEM	Infit	Outfit
Q1	49.1	0.19	1.37	1.29
Q2	35.6	0.40	1.05	0.76
Q3	66.7	0.16	1.08	1.18
Q4	40.5	0.26	1.06	0.98
Q5	48.6	0.21	1.31	1.36
Q6	39.6	0.28	0.87	0.66
Q7	44.1	0.25	1.02	1.14
Q8A	40.5	0.25	0.88	0.56
Q8F	40.5	0.24	0.95	1.44
Q8H	36.9	0.30	0.85	0.38
Q8S	41.9	0.22	0.85	0.56
Q9	36.5	0.41	1.08	0.94

Item	Calibration	SEM	Infit	Outfit
Q10	45.9	0.22	0.87	0.75
Q11	34.2	0.52	1.00	0.22
Q12	41.4	0.25	0.83	0.60
Q13	42.3	0.24	1.06	1.24
Q14	42.8	0.23	1.07	0.93
Q15	39.6	0.29	0.83	0.68
Q16	39.6	0.32	0.89	0.85

In this case we can see that item Q11 has significantly low Outfit value (0.22). The fit values for other item are within the productive range for developing measurement.

5.6. Reliability

We use Cronbach's alpha to assess the reliability of the measurement. Alpha values greater than 0.7 represent high reliability of the scale. The alpha value for the overall Index is 0.755. Cronbach's alpha values for each domain is presented in table 18. The reliability for health management is low but after eliminating the problematic item Q11 it is relatively acceptable. Small sample size might affect the reliability of this measure.

Table 18. Reliability of Heart Failure Index

Domain	Cronbach's Alpha
Patient Engagement	0.81
Symptom Recognition	0.71
Health Management	0.45

5.7. Construct Validity

We use Confirmatory Factor Analysis to validate the model of Symptom Recognition, Health Management and Patient Engagement. We use multiple goodness of fit indices such as relative χ^2, comparative fit index (CFI), the root mean square error of approximation (RMSEA), and Normed Fit Index (NFI) to assess the validity of each construct (Bozdogan, 1987; Steenkamp and Baumgartner 1998). A model is considered satisfactory if CFI $\geq$ 0.95, RMSEA $\leq$ 0.06, and NFI $\leq$ 0.90 (Gefen et al., 2000, Hu and Bentler, 1999). In case the result of the CFA analysis signal misfits for any of the constructs, we investigate Modification Indices to identify the problematic items. For Patient Engagement construct relative χ^2, CFI and NFI are within the acceptable range and we can conclude that the items are adequately measuring what they are expect to measure. CFA model for Patient Engagement is presented in Figure 22.

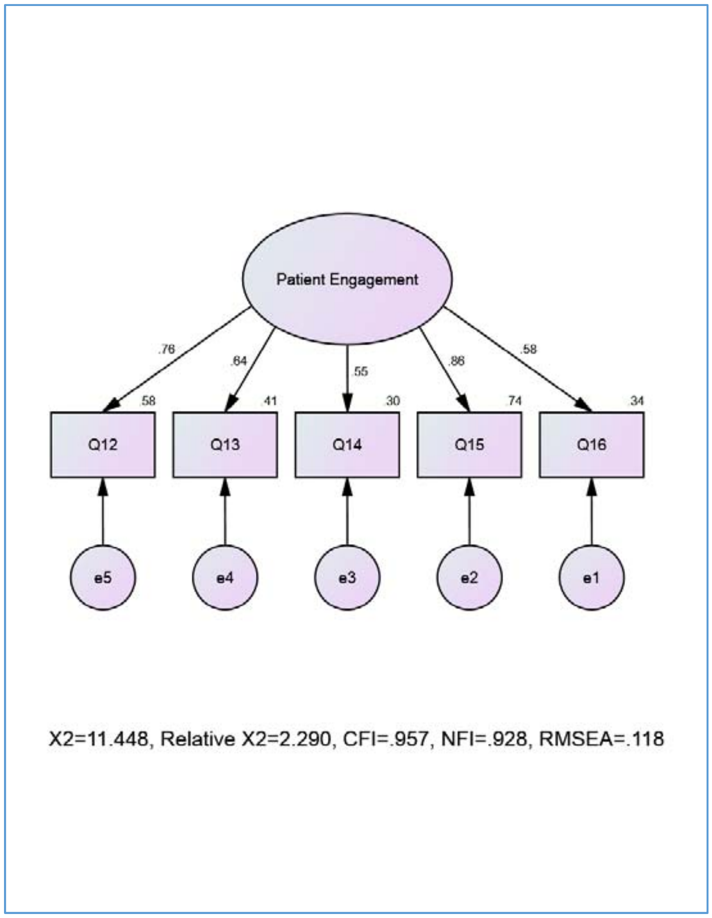


Figure 22. CFA for Patient Engagement

Model fit indices for Health Management are within the acceptable range. However factor loading for Q1 and Q3 are very low (-0.12 and -0.02 respectively). These results correspond with our misfit measures of the partial credit model. Figure 23 shows that model fit improves if we eliminate item Q1 and Q3 from the model.

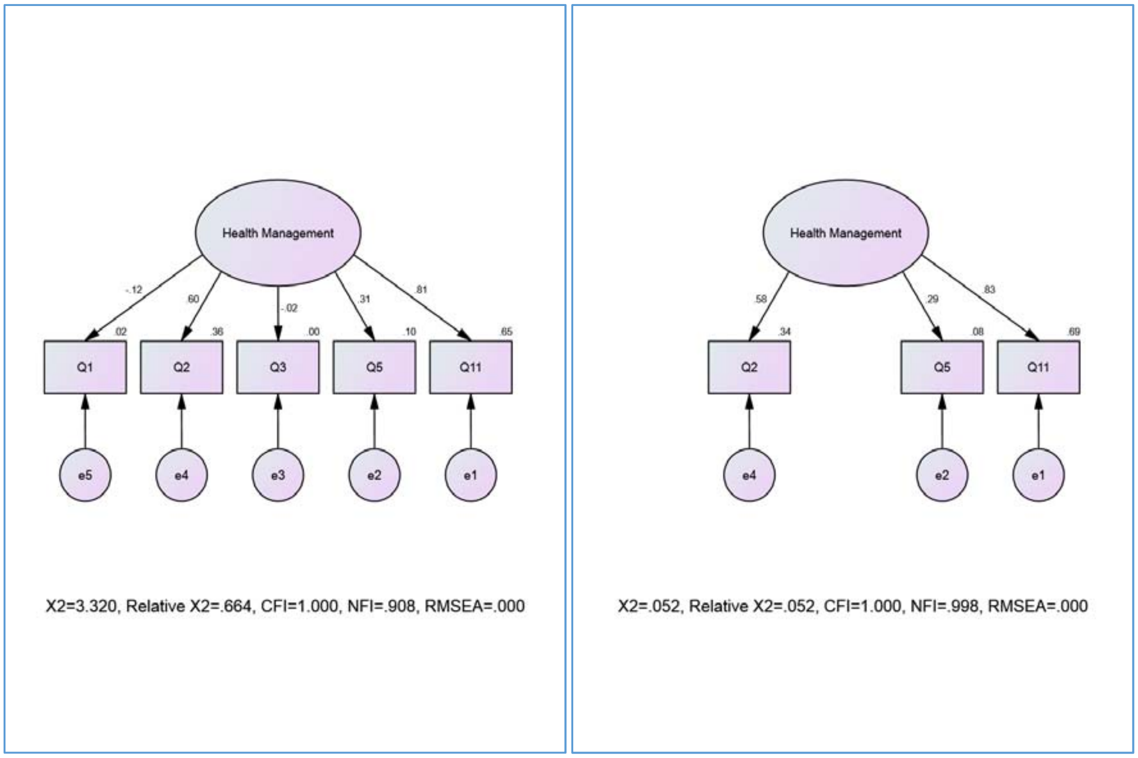


Figure 23. CFA for Health Management

Figure 24 shows goodness of fit indices for Symptom Recognition construct. Both CFI and NFI values are below the acceptable range (0.69 and 0.60 respectively). Looking at modification indices suggest that item Q8Stomach and Q9 should be eliminated from the model to improve the model validity. Elimination of these two items leads to a better construct fit.

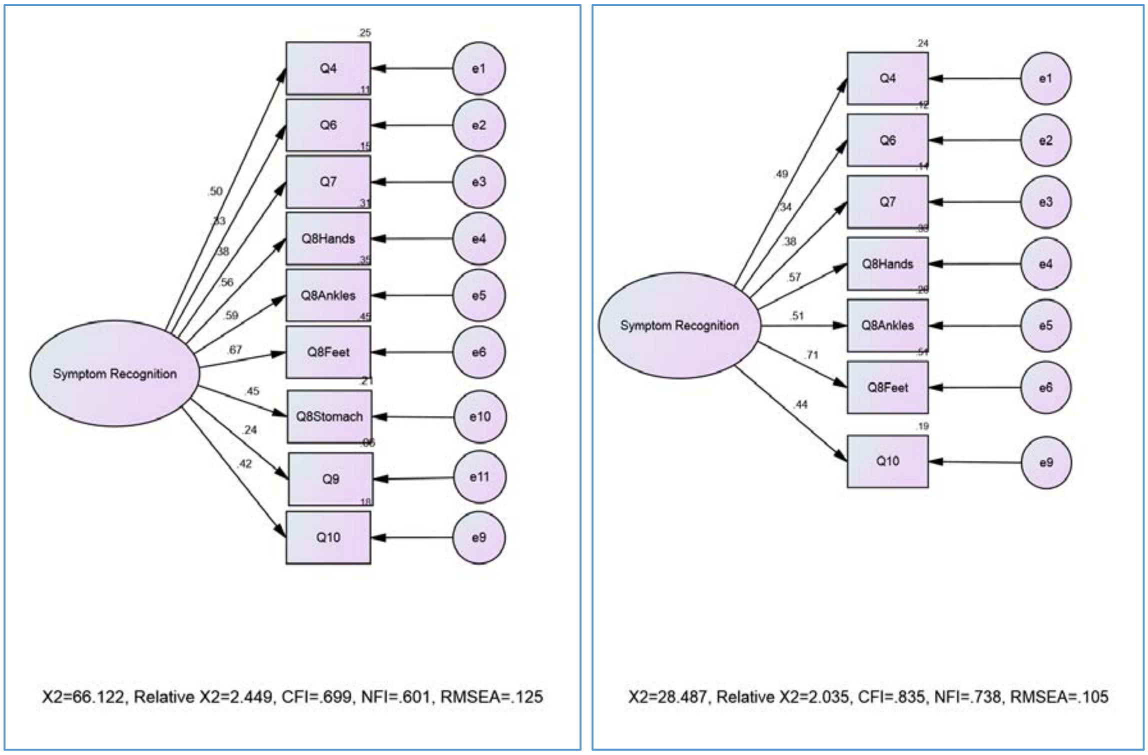


Figure 24. CFA for Symptom Recognition

5.8. Conclusion

The purpose of this study was to develop a more comprehensive version of heart failure index that assess both physical and psychological symptoms of patients and evaluate its reliability and validity to be the fundamental component of an mHealth tool for patients with heart failure. Based on out review of literature and discussions with a panel comprise of cardiologists and physician assistants, we identified three important domains to develop heart failure index: Symptom Recognition, Health management and Patient Engagement. The experts constructed a pool of 19 items. We performed 2PL model as well as partial credit model to assess item functionalities. We have also test the reliability and validity of the measurement. The results of analysis on a pilot of 100 respondents reveal that three items can be eliminated from the index: Q1, Q11 and Q8S. Q8 refers to recognition of swelling around stomach. Q1 refers to changes in patients' weight. This might be due to the fact that majority of the patients do not have access to a scale to trace their weight changes on a daily basis. Q11 refers to keeping up with appointments. The data collection for this study occurred inside heart failure clinic and majority of the respondents were in the clinic with an appointment. Therefore, the variability in range of responses for this item was scares.

In conclusion, we developed a parsimonious assessment index with lower number of items compare to the current indexes available in the market with high reliability and validity measures. This HF index includes both physical and psychological conditions of the patients with heart failure and helps care providers to understand and evaluate their patients more accurately. This instrument is the foundation of an mHealth tool that hope to improve the quality of care for patients with heart failure and inform their decisions to avoid preventable readmissions and ER visits.

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