Toward a Healthcare Services Ecosystem

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Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in
Business Information Technology

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March, 14 2018
Blacksburg, Virginia

Keywords: Healthcare, Resilience, Analytics, Usability

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Abstract

This research examines the healthcare services ecosystem and the impact and role service interventions made by providers and patients have on this ecosystem. Each area has an important role in contributing to the value and sustainability of the ecosystem. Healthcare, as a community service, requires a minimum of two counterparts: the providers and the customers, in this case the patients. Healthcare is a unique ecosystem because often the customers are not conscious of the interplay of the ecosystem but are reliant upon the system for their health and wellbeing.

The first section of this dissertation examines the effects that occur in the healthcare ecosystem when part of the system experiences a disaster and the impact and role of other areas of the system in response to the disaster, particularly regarding the resilience. Similar to a biological ecosystem that is undergoing a flood, in the healthcare services ecosystem if too many patients present to the Emergency Department (ED) at the same time disaster level overcrowding will occur. We aim to measure the resilience of the healthcare ecosystem to this disaster level overcrowding.

The second section of this dissertation examines how the components of the healthcare ecosystem maintain sustainability and usability. Healthcare professionals are assessed regarding their ability to maintain the healthcare ecosystem, with a specific focus on what occurs after patients are in the hospital system. To examine the ability of the healthcare professionals to

maintain the ecosystem we analyze the usability and adaptability of the electronic health record and the professional's workflows to determine how they use this tool to sustain the healthcare ecosystem.

The third section of this dissertation examines patient self-management and the influence this has on the healthcare ecosystem. Much of the management of health in patients, particularly those with chronic illnesses, occurs outside of the hospital, thus examining this aspect of self-care provides insight on the overall system. This research examines patients with a chronic illness and their use of online health communities, with a particular focus on their reciprocal behaviors and the impact this support system has on their overall health state. By examining these aspects of the healthcare services ecosystem, we can better improve our understanding of these phenomena.

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General Audience Abstract

This dissertation examines healthcare as an ecosystem to discover how various aspects interact with each other. The first section looks at emergency department overcrowding to examine the resilience to determine the causative and mitigating factors. The second section examines the electronic medical record for usability and determines the most impactful factors for healthcare workers. The third section examines online health communities with consideration of reciprocal behaviors and their impact on users' health. Consideration of the healthcare ecosystem and the broad applicability of this topic provides researchers with an overarching framework for future work.

Acknowledgments

I would like to thank the many people that assisted in the completion of this dissertation. My advisor, Dr. Lara Khansa, for inspiring me to perform high level research in her Health Information Technology class and since joining the Ph.D. program the invaluable feedback and guidance which helped in strengthening each of the papers. I would also like to thank Dr. Christopher Zobel for introducing the concepts of resilience and service science, both of which were primary motivators for this dissertation, as well as always reading and providing constructive criticism for each of the papers we have worked on. I would like thank Dr. G. Alan Wang for his seminar class that taught me all the necessary parts of a research paper and the importance of theory and theoretical contribution when writing high-level academic papers. I would like to thank Dr. Cliff Ragsdale for his personal touch when admitting me to the Ph.D. program, as well as his inspiration for future research with regard to DEA and fee-for-outcome healthcare reimbursement. I would like to thank Dr. Alan Abrahams for his assistance in understanding text-mining research and for helping in the design of the healthcare services ecosystem framework presented in chapter 1 of this dissertation.

I would like to thank family, and in particular my wife, for their support while completing my Ph.D. I could not have finished without the love and support of my wife, Heather Davis. She has read, not quite tirelessly, over each of my papers and helped me in many instances along the way in the completion of this dissertation. Finally, I would like to thank my son Zachary Davis II for providing the encouragement and foundation to pursue a Ph.D. in hopes of providing him a better and more enriching future.

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Chapter 1: Introduction

The healthcare ecosystem is a network of interconnected systems comprising of healthcare professionals, payers, patients, IT services, medical equipment and pharmaceutical companies (Bahga & Madisetti, 2013). Service relationships between these entities are key to bringing research into practice and improving care. The healthcare services ecosystem focuses on engaging the community, clinical staff, and researchers who use health information technology services to improve communication and performance (Carroll, et al., 2009). The goal of healthcare is to increase patient-centric care coupled with improving communication across care delivery settings from self-care in the home, to outpatient care, to the hospital, and to rehabilitation services (Serbanati, Ricci, Mercurio, & Vasilateanu, 2011).

In the past, the emphasis of the healthcare system has been on service provider preferences and the shift to a more collaborative, patient-centered healthcare services ecosystem provides many areas for change and improvement (Binczewski, Kurowski, Mazurek, & Stroninski, 2011). Understanding how the healthcare system can streamline and optimize care delivery processes is imperative to improving the patient experience and the care they receive (Serbanati & Vasilateanu, 2011). There is an increased awareness of the role of information technology and the ability for that technology to improve communication and patient care as the healthcare system moves toward patient centrality (Binczewski, Kurowski, Mazurek, & Stroinski, 2011). This dissertation examines three specific perspectives of IT services utilized in healthcare to ascertain the impact on the overall patient experience in the provider-customer relationship. We adapt the framework by Spohrer, Maglio, Bailey, and Gruhl, (2007) to consider the healthcare service ecosystem, see Figure I.

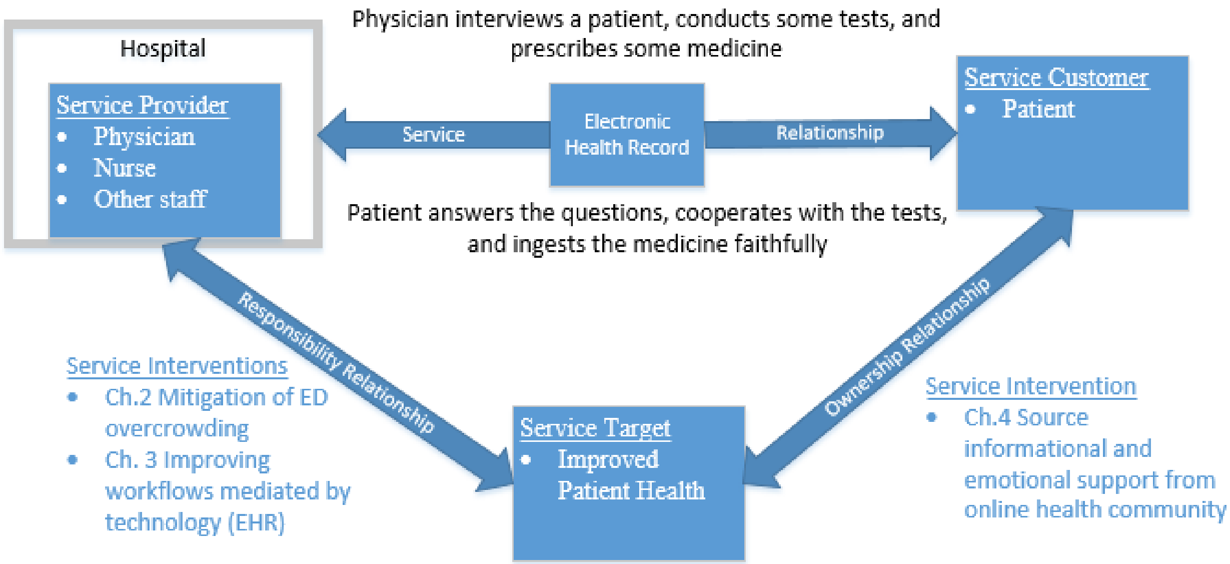

Figure I Service System Interventions adapted from Spohrer, Maglio, Bailey and Gruhl (2007)

In the model, the service provider and service customer have a service relationship with the goal of value creation. The service target is the reality to be transformed or operated on by the provider for the sake of the customer. In this dissertation, we examine service system interventions made by the service provider in the form of the responsibility relationship and the service system interventions made by the service customer in the form of the ownership relationship. We inspect the responsibility relationship by specific IT services for healthcare as the service provider, the hospital staff, contends with two situations: when customer demand outstrips available supply and when technological mediation of the service relationship is not optimized. We investigate the ownership relationship by viewing an IT service that is utilized when the service customer, the patient, has to take ownership in order to source the service they need due to a service relationship breakdown. The service target for the healthcare service ecosystem is the value created by insuring proper care and improved health of the patient.

In the macrocosmic scope, this dissertation provides new perspectives on the IT service system within the specific organizational context of the healthcare business. Service science is an ideal framework for studying the relationships between provider and customer in healthcare. In the healthcare service system, we examine three perspectives on factors that affect this service relationship. The service system can be analyzed to discover the impact of increased demand and then how the provider meets this increased demand. Next, we can evaluate how technology mediates the service relationship by examining the usability and adaptation of the technology used to improve the service relationship. Finally, we probe the service system examining it when a breakdown occurs in the service relationship and then to determine how the customers seek the service they require from a new source. This dissertation contributes to the stream of literature in service science and each chapter makes individual contributions outlined in the next several paragraphs.

The first perspective of the service system we delve into is how increased demand effects the service relationship. Patients can present to the healthcare system in a variety of ways including primary care, specialty care, urgent care, or emergency care, among other platforms. The healthcare service system is often not prepared for the increased service demand resulting from the rapid influx of patients that present for care, resulting in delays that are detrimental to patient health and satisfaction. To address this increased demand for ED services, our research focuses on introducing and quantifying a new measure of resilience in the ED setting, examining the effects of the variables in play, and determining a method for predicting imminent disaster level overcrowding. We develop the novel concept of component resilience and provide a granular model that quantifies the impact of each factor contributing to an overcrowding event. We believe that this novel concept of component resilience makes a significant theoretical contribution to the field. Our component resilience model builds on existing work to capture dimensions of the overall recoverability and overall resistance of the system at a more granular level. Assessing resilience at this granular level allows decision makers to pinpoint which components of the system should be improved to increase the resilience to disaster level overcrowding.

Another aspect of the healthcare service ecosystem that influences patient-centric care is the electronic health record (EHR), utilized as a technological mediator in the provider-customer service relationship. As use of the EHR is mandatory across healthcare settings the usability and functionality of it has increased in importance in relation to the healthcare services ecosystem (U.S. Department of Health and Human Services, 2009; Centers for Medicare and Medicaid Services, 2016). The EHR provides a method of documenting and communicating patient care across healthcare settings, which impacts overall patient care and the healthcare ecosystem. The EHR's role in patient care is often not one perceived by patients, despite the integral role it plays. We advance a new framework built on the theory of reasoned action while adapting and extending recent work on usability. The EHR focuses on improving the safety and quality of the care patients receive and thus maximizing usability for healthcare professionals is paramount (Bahga & Madisetti, 2013). Patients do not use the EHR but the impact it has on overall patient care and the management of each individual patient's care is great. Understanding how the EHR is adapting to better align with the intended use of the technologically mediated service relationship will provide new insight into theory.

The third aspect of the healthcare ecosystem we inspect is how customers seek a new source of value creation when the traditional provider-customer service relationship breaks down. Patients seek advice regarding their healthcare management in a variety of ways, including collaboration with healthcare providers. The primary source of information and support for patients prior to the internet was their healthcare providers and their personal social support system. As the internet has become widely available patients have been able to access large amounts of static health information and with web 2.0 they have been able to take part in creating information, relationships, and communities (Woo, Lee, Ku and Chen, 2013). The creation of online health communities has given patients and their caregivers a place to seek support and information; however, the impact on their health resulting from the use of these communities is uncertain. We advance a new framework to understand how different kinds of reciprocity moderate the process of receiving social support and obtaining value creation in the form of improved health. Health management at home is a key part of the overall healthcare ecosystem and understanding online health communities' impact is important to understanding self-management of patients with chronic illnesses (Yan and Tan, 2014). By understanding how online communities fill a void found in the traditional healthcare service system we advance a new theory of reciprocity's effect on social support toward improved health.

With so many interacting factors making up the healthcare services ecosystem, many avenues for research and improvement exist. We now discuss, in more detail, the three main contributions of this dissertation.

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Chapter 2: Emergency Department Resilience to Disaster Level Overcrowding: A Component Resilience Framework for Analysis and Predictive Modeling

1. Introduction

According to a 2009 report from the United States Government Accountability Office, the national average wait time to see a physician in the emergency department (ED) is often twice the recommended time (U.S. Government Accountability Office, 2009). In a 2010 report, Press Ganey reported that the average ED wait time in the US was 4 hours and 7 minutes in 2009 (Press Ganey, 2010). Many emergency departments routinely face overcrowding, which is defined as the condition where the demand for emergency services outstrips the available resources of supplies, staff, and space (Bellow & Gillespie, 2013; Hwang & Concato, 2004; Fatovich, Nagree & Sprivulis, 2005). Severe or extreme overcrowding scenarios are referred to as disaster level overcrowding. Often these scenarios are not actually associated with any natural or manmade catastrophe but are quantitatively defined using a standardized index, as we will discuss below. However, disaster level overcrowding is more common than the name implies: healthcare systems worldwide experience the effects of disaster level overcrowding in their emergency departments on a recurring and surprisingly regular basis (Shih et al., 1999; Pines et al., 2011).

The effects of ED overcrowding are severely detrimental to health and safety in the community that the healthcare system serves. Overcrowding inhibits safe and timely care by decreasing health care accessibility and increasing the likelihood of patient mortality and morbidity (Hoyle, 2013). In addition to decreasing the quality of care, ED overcrowding also increases healthcare costs. Patients that could be treated at a lower cost in an inpatient unit continue to take up higher-cost space in the ED when no inpatient beds are available. Staff experience increased burnout, and hiring and training replacement staff is costly. Patients that could have been treated at the hospital are sent elsewhere, resulting in lost business for the hospital. Overcrowding also creates a poor image of the hospital in the community, which may prompt patients to seek care elsewhere, potentially resulting in both revenue loss for the hospital and a negative impact on patient health if patients travel further for treatment (Handel et al., 2010; Sun et al., 2013; Foley, Kifaieh and Mallon, 2011). These negative effects for patients and providers are naturally exacerbated as overcrowding approaches disaster levels.

The problem of overcrowding seems simple to define: the more people that present to the emergency department, the longer it takes for people to receive care. A rapid presentation of patients to the emergency department, referred to as patient surge, is commonly cited as the cause of overcrowding. In reality, however, overcrowding is far more complicated. As we discuss in more detail below, five major factors contribute to ED overcrowding: ambulance diversion, boarding patients in the emergency department when they need to transfer to an inpatient floor, patients leaving without treatment, increased number of patients, and increased waiting times (Bellow & Gillespie, 2014). Compounding factors may include a lack of capacity in the observation area, opinions of staff on overcrowding, bed ratio, acuity ratio, provider ratio and demand value (Hwang & Concato, 2004). With all of these considerations in play, it becomes obvious that overcrowding is not simply caused by lack of space in one hospital department, but is rather a multifaceted problem that is connected to the system as a whole.

To better understand this complex phenomenon, this study analyzes multiple, related instances of disaster level ED overcrowding. Currently, a method does not exist that would allow us to compare features of independent disaster events to each other. We therefore develop an analytical framework and quantitative model based on the concept of disaster resilience. In a healthcare context, resilience is defined by the Agency for Healthcare Research and Quality (AHRQ) as “the ability of systems to mount a robust response to unforeseen, unpredicted, and unexpected demands and to resume or even continue normal operations” (Nemeth, Wears, Woods, Hollnagel and Cook, 2008). We utilize the AHRQ’s definition to encompass the factors that have been found to impact the emergency department’s resilience, multidimensionality, and ability to return to ideal functioning. This allows us to explicitly examine the factors precipitating overcrowding events, which will better enable decision makers to make targeted improvements in the ED and other departments. A resilience perspective offers a holistic view of the system’s behavior during the recovery process by capturing both the loss and recovery time, uncovering aspects of system behavior that might not otherwise be visible. Calculating resilience, especially in the context of an emergency department that regularly experiences disaster level overcrowding, will optimize the hospital’s reaction to disaster level events and save time, money, and lives.

Our research therefore focuses on quantifying resilience in the ED setting, examining the effects of the variables in play, and determining a method for predicting imminent disaster level overcrowding. We develop the novel concept of component resilience and provide a granular model that quantifies the impact of each contributing factor to an overcrowding event. When used by hospital decision makers, this model facilitates exploration of mitigating factors and targeted interventions that can improve the resilience of the emergency department, preventing or diminishing the effects of overcrowding before it occurs. Our model also allows administrators to determine the best mitigating action or intervention at any point in time, pre-, mid- or post-event, to return to a state of equilibrium. This quantitative analysis of resilience facilitates direct comparison of strategies aimed at improving the overall resilience of the system, of methods chosen to respond to individual overcrowding situations, and of potential administrative decisions.

In the following section, we present a literature review that delves into overcrowding scores and contributing factors. We then explain how we redefine predicted resilience in the ED setting by adapting the resilience model of Zobel (2010). Next, we explain the data set, key variables, and methods of data analysis. We subsequently present the results and discuss our findings, and, lastly, we discuss our study's implications, limitations, and suggestions for future research, including how our resilience measures can be applied to other areas of hospital management.

2. Literature Review

We review the literature by first considering relevant research on the development of ED overcrowding scales and then discussing the relevant literature on resilience.

2.1 Emergency Department Overcrowding

We begin the discussion on overcrowding by looking at its definitions and contributing factors as described in the extant literature. Bellow and Gillespie (2014) defined ED overcrowding as: "A situation in which identified need for emergency services outstrips available resources in the emergency department, hospital or both." As noted earlier, this paper uses a modified definition of ED overcrowding as outlined by the hospital administration through our partnership: a condition where the demand for emergency services outstrips the available resources of supplies, staff and space. ED overcrowding is generally associated with patient surge[1] and surge capacity[2].

Bellow and Gillespie (2014) also identify primary factors behind ED overcrowding. According to this study, the primary hospital factor impacting ED overcrowding is a lack of available inpatient beds for patients that enter the hospital through the ED, and the primary external factor is ambulance diversion (Bellow and Gillespie, 2014). A number of studies have also noted boarding as a prominent cause of ED overcrowding (Weiss et al., 2005; Bair, Song, Chen and Morris, 2010; Felton, Residorff, Krone and Laskaris, 2011). Boarding is defined as a condition in which a patient needs to be transferred from the ED to an inpatient bed, no bed is available, and the patient remains in the ED, occupying an ED bed even though they no longer require ED level care. An increase in boarding creates a dysfunctional environment for ED staff because the ED is not equipped to provide the specialty care that is available on an inpatient unit. Adkins and Werman (2015) noted that if an emergency department can decrease boarding times, ambulance diversion times will also decrease. The turn-around time associated with ambulance offload to ED door time has also been identified as a factor behind ED overcrowding. When the ED is already at or beyond capacity, there is no place for the patients in the ambulance to be offloaded. Patients may remain on the ambulance, preventing the ambulance from assisting other patients. Cooney, Wojcik, Seth, Vasisko, and Stimson (2013) found that improving turn-around time also improves the National Emergency Department Overcrowding Scale (NEDOCS) score and assists decision makers to accurately determine when ambulance diversion is necessary.

[1] Patient surge describes the ability to provide adequate medical evaluation and care during events that exceed the limits of the normal medical infrastructure of an affected community (U.S. Department of Health and Human Services, 2012).

[2] Surge capacity refers to the ability to evaluate and care for a markedly increased volume of patients—one that challenges or exceeds normal operating capacity (U.S. Department of Health and Human Services, 2012).

Overcrowding not only affects the quality of patient care, but it increases the costs of care in a variety of ways. Delays in care occur because of the overcrowded ED and often result in a longer recovery time and increased length of stay for patients. When the length of stay extends beyond the days covered by insurance or if the patient is indigent, costs increase. The hospital may also face fines for delays in care if legal standards are not met, as in the treatment of stroke and cardiac arrest patients. When ambulances need to be diverted, patients are sent to other hospitals and thus the revenue from those patients is lost. As patients received through the emergency department generally result in a higher level of revenue, the loss of those patients to another facility results in greater revenue losses than the loss of patients directly admitted from another source. Additionally, ED overcrowding contributes to staff burnout. With a current shortage in most healthcare professions, acquisition of new staff is challenging; moreover, there are increased costs associated with hiring and training new staff. The identification and mitigation of ED overcrowding is thus a priority in the ED (Richardson and Ardagh, 2005).

The NEDOCS score is the most prevalent measurement used in emergency departments in the United States to determine the level of ED overcrowding. In addition to NEDOCS, several other methods for quantifying overcrowding have been developed, including EDWIN (Emergency Department Work Index), READI (Real-time Emergency Analysis of Demand Indicators) and EDCS (Emergency Department Crowding Scale). These scales have been independently evaluated by several studies (Jones, Allen, Flottemesch and Welch, 2006; Hoot, Zhou, Jones and Aronosky, 2007; Weiss, Ernst and Nick, 2006). Each of these studies compared the methods of quantifying overcrowding and found that although each has varying levels of sensitivity, the NEDOCS is the most sensitive in detecting overcrowding. McCarthy, Ding, Pines and Zeger (2011) found that the more frequently NEDOCS measurements are taken, the more likely it is that the results correlate to ED crowding and ED length of stay.

Since NEDOCS contains objective measures that can be analyzed and provides association with the variables that can be manipulated to improve ED resilience, we determine NEDOCS to be the most appropriate tool for our study. Variables necessary to calculate a NEDOCS score include the number of ED patients, number of ED beds, number of inpatient beds, last door to bed time, longest admit time, and number of critical care patients in the emergency department. The algorithm developed by Weiss et al., (2004) is presented below (See Equation 1).

$$NEDOCS(t) = -20 + 85.5\left(\frac{L_{ED}(t)}{b_{ED}(t)}\right) + 600\left(\frac{L_{admit}(t)}{b_h(t)}\right) + 5.64W_{ED}(t) + 13.4L_{rp}(t)$$

Equation 1

The definitions of the terms presented in the NEDOCS are as follows:

- $L_{ED}(t)$: Total number of patients in ED occupying beds, including hallway beds
- $b_{ED}(t)$: Total number of ED beds
- $L_{admit}(t)$: Number of ED patients waiting to be moved from ED to hospital
- $b_h(t)$: Total number of occupied and vacant inpatient beds in the hospital
- $W_{ED}(t)$: Waiting time from triage to ED bed placement
- $W_{admit}(t)$: Longest boarding time of patients within the ED waiting to be admitted to the hospital
- $L_{rp}(t)$: One-third of total number of patients admitted to adult ICU beds – representing estimated aggregate acuity of patients within the ED

2.2 Disaster Resilience

Recent top level operations management research has primarily focused on resilience as it pertains to supply chain disruptions, critical infrastructure, and quality disruptions (Ambulkar, Blackhurst, and Grawe, 2015; Su, Linderman, Schroeder, and Van de Ven, 2014; Kim, Chen, and Linderman, 2015; Liu, Song, and Tong, 2016; Besiou, Pedraza-Martinez and Van Wassenhove, 2014). However, there is insufficient research in operations management on the resilience of healthcare systems. Filling this void in healthcare resilience research is especially critical because a healthcare facility, and an emergency department in particular, is an example of a socially responsible operation that would benefit from a method to model resilience and inform decision making in overcrowding scenarios.

Bruneau et al. (2003) first quantified resilience by measuring seismic resilience as the integration of the loss of quality with respect to time. This study further attributed resilience to four dimensions: robustness, redundancy, resourcefulness and rapidity. Robustness and rapidity are the quantifiable aspects of resilience, and redundancy and resourcefulness are the 'means' in which to improve resilience (Bruneau et al., 2003). See Figure 1 for the original resilience triangle.

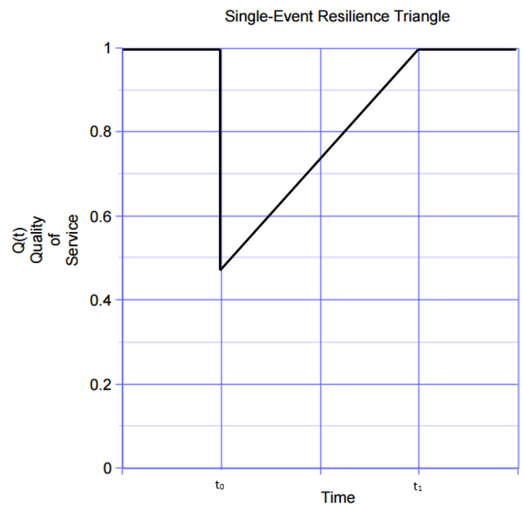

Figure 1: Single event resilience triangle adapted from Bruneau et al., 2003

Bruneau et al. (2003) calculated the loss of resilience by quantifying the area above the quality curve as the integration of the functionality lost at t_0 until the recovery time at t_1. See Equation 2.

$$R = \int_{t0}^{t1} [100 - Q(t)]dt$$

Equation 2

We also use Bruneau's terminology, adapting it for our unique application. Bruneau et al. (2003) utilized the terms robustness and rapidity, and we define those here to lay the foundation for our extrapolation. Robustness is "the strength of a system, or its ability to resist the impact of a disaster event, in terms of the amount of damage or loss of functionality that results because of that event" (Bruneau et al., 2003); and rapidity is "the rate or speed at which a system is able to recover to an acceptable level of functionality, after the occurrence of a disaster event" (Bruneau et al., 2003). Robustness and rapidity are two important aspects of the system that provide the decision maker with the ability to make changes that can impact resilience. We re-term and redefine these concepts as resistance and recoverability: we define resistance as the ability to withstand system functionality lost, and recoverability as the amount of time it takes to return to normal system functionality.

Our theoretical framework is also informed by the work of Zobel (2010), who extended the work of Bruneau et al. (2003) by creating the concept of predicted resilience. Predicted resilience is expressed as a percent of the calculated resilience from the upper bound of an acceptable recovery time, T* (See Figure 2).

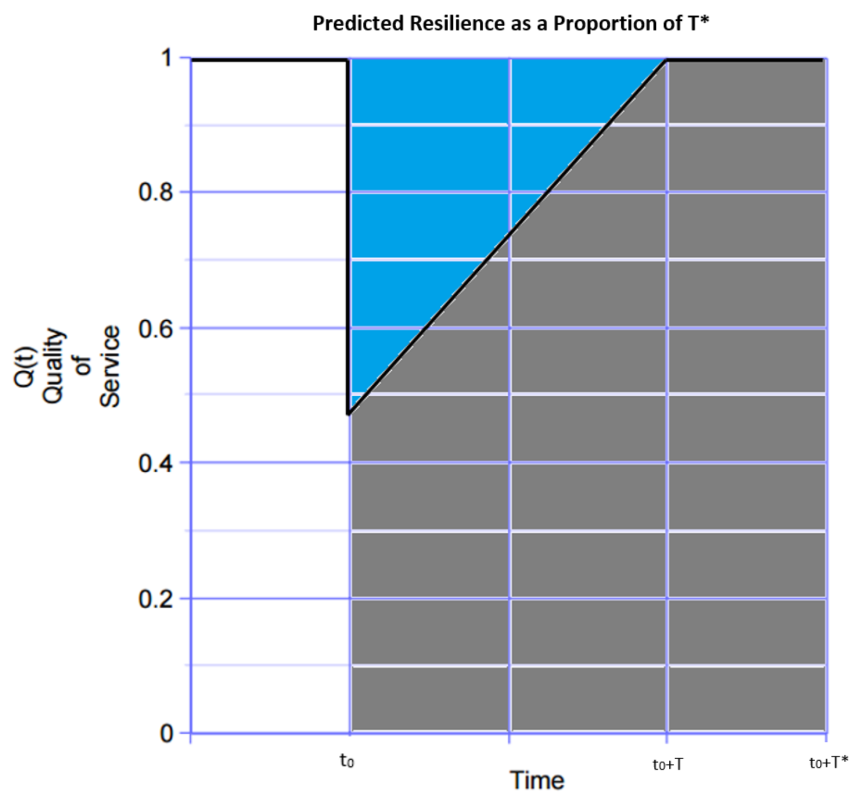

Figure 2: Predicted Resilience adapted from Zobel, 2010

The actual value of T* can be decided with regard to a particular decision maker for a desirable recovery time, assuming linear recovery and instantaneous loss. See Equation 3.

$$R(X,T) = 1 - \frac{XT}{2T^*} \; X \; \in [0,1], T \in$$

Equation 3

In 2011, Zobel extended the predicted resilience concept to allow decision makers to adjust the resilience system according to their preference (Zobel, 2011a). Zobel and Khansa (2012) re-interpreted predicted resilience to account for slow onset situations. Zobel and Khansa (2014) further extended their research to include multiple event disasters, allowing the following calculation (see Equation 4).

$$A_i = (t_{i+1} - \; t_i)(X_i + x_i')/2$$

Equation 4

The above equation gives the trapezoidal approximation of the area below the curve. Each result is then summed to give the total area below the curve. The ratio of the area A to the area in the time interval of T* is found. We are then able to generate predicted resilience to a multi-event disaster with the following equation (see Equation 5).

$$R = \frac{A}{T^*}$$

Equation 5

The predicted resilience curves are generated to compare scenarios as shown in Figure 3. Plotting the loss and recovery time allows a decision maker to juxtapose loss and recovery values that have the same predicted resilience value.

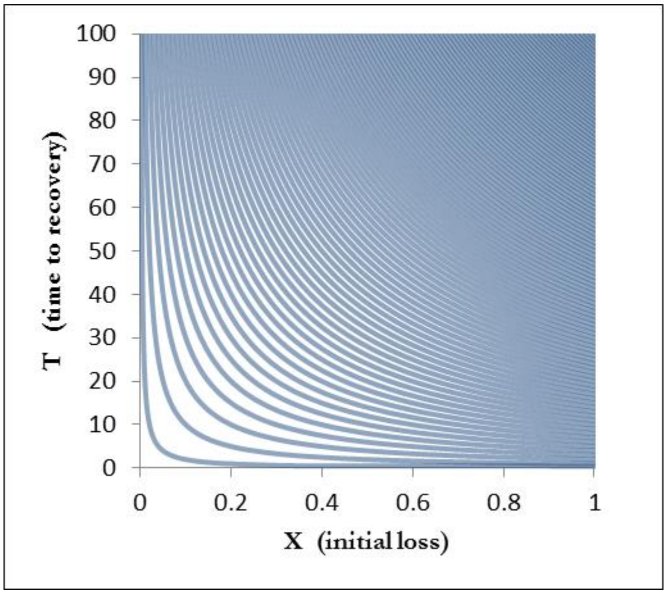

Figure 3: Predicted resilience curves adapted from Zobel (2011a)

Our study extends the work of Zobel (2010; 2011a) and Zobel and Khansa (2012; 2014) on predicted resilience by applying it to the specific case of an emergency department and to the specific scenario of disaster level overcrowding. We also examine extensions of the multidimensionality of resilience to develop an abstract multi-dimensional framework to analyze overall system resilience. In our study, we utilize the conceptual realization of multi-event disaster resilience as quantifying predicted resilience against disaster level overcrowding. The value in calculating the predicted resilience for each disaster event is that it allows for a direct comparison of different disaster events on the same relative scale. Afterwards, we can identify variables that may predict disaster level overcrowding and allow for opportunities for mitigation. We develop our research questions by aligning this background with the needs of the emergency department as identified through our partnership. Our primary research question is: How can resilience be quantitatively measured in the emergency department and what decisions can be made by the administration to improve this resilience? We also ask: Do factors exist that can be evaluated to predict a disaster level overcrowding event before it occurs?

Currently the Carilion Clinic utilizes the NEDOCS scores to identify a disaster state and implement a code yellow. This determination is made by the unit director in the ED, in consort with administrators in the transport unit and emergency management. When the NEDOCS score exceeds 180, the level of overcrowding is said to have reached disaster level and the ED unit director calls a code yellow, beginning a process that aims to return the ED to a pre-disaster level of crowding. The creators of the NEDOCS set a score of 180 as a standard for disaster level overcrowding (Weiss et al., 2004), and Carilion Clinic, the setting of our study, has validated this number. One hundred and eighty is also the NEDOCS score at which Carilion Clinic implements a code yellow. Our research therefore examines the hospital system in this disaster state.

A code yellow message is announced over the hospital's public address system, alerting staff to the need to prepare for an emergency and decompress the emergency department by discharging inpatients more quickly and moving ED patients to the inpatient beds. A code yellow also allows hospital staff to be redistributed to transfer patients faster (Hoyle, 2013). A code yellow is not a universally applied code status; however, it is used at many medical centers. With our research, we introduce an application of the predicted resilience model, using the NEDOCS scores, that allows us to quantify resilience in the emergency department, develop a decision support system for use by administrators in the ED, and potentially prevent the calling of a code yellow.

2.3 Multidimensional Resilience

Zobel (2011b) examined the multidimensional nature of disaster resilience by differentiating how the physical, organizational, social, and economic dimensions of a system respond to a disaster. The idea is that both resistance and recoverability can be measured separately within each of these dimensions, and the combined results can then provide a comprehensive picture of the system's overall resilience from several different perspectives.

Our application of the resilience measure to the emergency department extends the idea of multidimensional resilience in a slightly different way, by focusing on a single dimension: organizational resilience. We then hierarchically group together different indicators of resilient behavior according to whether they are directly associated with the impacts of a disruption or with the recovery time. By taking such a perspective on resilience, not only can we observe the overall resilience, as indicated by the observed calculated resilience of the entire ED system, but we can also view a representation of the overall resistance and recoverability as latent variables with their own associated indicator variables.

Viewing resilience from this perspective allows for a cascade of analyses to occur on component level resilience. Each indicator variable that is used to understand a latent variable will have a component resilience value that can further be examined with its own measures of resistance and recoverability, giving the true overall resistance and recoverability at the component level. As a specific example of this, we present the healthcare system model in Figure 4.

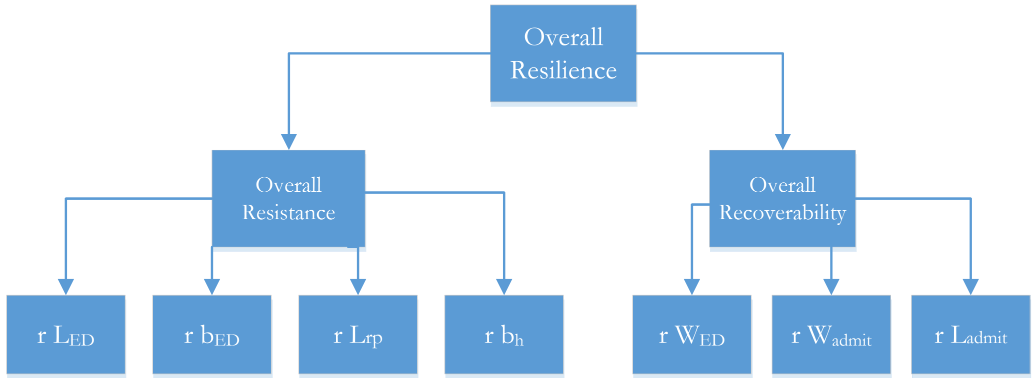

Figure 4: Example of hierarchal multidimensional resilience with component resilience

The variables of $\mathbf{rb_h}$ and $\mathbf{rb_{ED}}$ are constant, as the total number of beds in the hospital and total number of beds in the ED do not change during the time period of our study and are thus not included in our component resilience measures. The component resiliencies $\mathbf{r_{LED}}$, $\mathbf{r_{Lrp}}$, $\mathbf{r_{Ladmit}}$, $\mathbf{r_{WED}}$ and $\mathbf{r_{Wadmit}}$ are thus categorized into resistance-related and recoverability-related measures. The use of the lowercase letter **r** signifies that these resilience indicators are at a lower level in the hierarchy than the uppercase **R**s of overall resilience, based on the retroactive decision policies in place. Since $\mathbf{r_{LED}}$ and $\mathbf{r_{Lrp}}$ are strictly count-based, they are judged to have more to do with the resistance of the system, and since $\mathbf{r_{Ladmit}}$, $\mathbf{r_{WED}}$ and $\mathbf{r_{Wadmit}}$ are associated with throughput or waiting times, it follows that they are associated with delays in the recoverability of the system. This conceptualization extends previous views of resilience by allowing for the various component measures of resilience to be examined at an increasingly granular level, with each dimension allowing for more analysis to be performed and thus contributing to a clearer picture of the disaster event.

3. Data and Methods

Operational data was collected from the emergency department at Carilion Clinic, a large academic medical center, over a one-month period. Carilion Clinic is the only level one trauma center in the region and serves nearly one million community members in southwestern Virginia (Carilion Clinic, 2015). The data we collected includes:

- NEDOCS scores (as well as the component data used to calculate the NEDOCS scores) recorded every 15 minutes for the entire month
- The number of ED beds in use by hour
- Throughput timestamps (starting with arrival time to ED, time to ED bed, time to physician disposition and time to floor bed)
- Staffing schedule

These pieces of data were each identified by the administrators at the academic medical center as data they collect to make decisions about everyday management in the emergency department as well as when managing a disaster overcrowding event.

To examine the resilience of the emergency department, we first interviewed various administrators, including vice presidents, executives, chairs of the emergency department, departmental directors and ED unit directors. From these interviews, we were able to determine which types of data would be most relevant in quantifying the emergency department’s resilience to overcrowding. According to the interviewees, the most important pieces of data identified and collected are the NEDOCS scores and associated component data. These interviews also allowed us to gain a clear picture of the needs of the ED in overcrowding situations, particularly regarding the need for the administrators to be able to identify the most impactful areas and the information needed to create a predictive model.

We analyzed one month of the NEDOCS scores and, aligning with the findings in the literature, we found many instances of disaster level overcrowding. Figure 5 shows the NEDOCS scores for the emergency department for each day of the month, with the horizontal line depicting the threshold for disaster level overcrowding. In examining the data with respect to this threshold, we can see that disaster level overcrowding occurred on 13 out of the 31 days in May. Although this is a relatively high occurrence of disaster level overcrowding, such a rate of overcrowding is not uncommon at this facility.

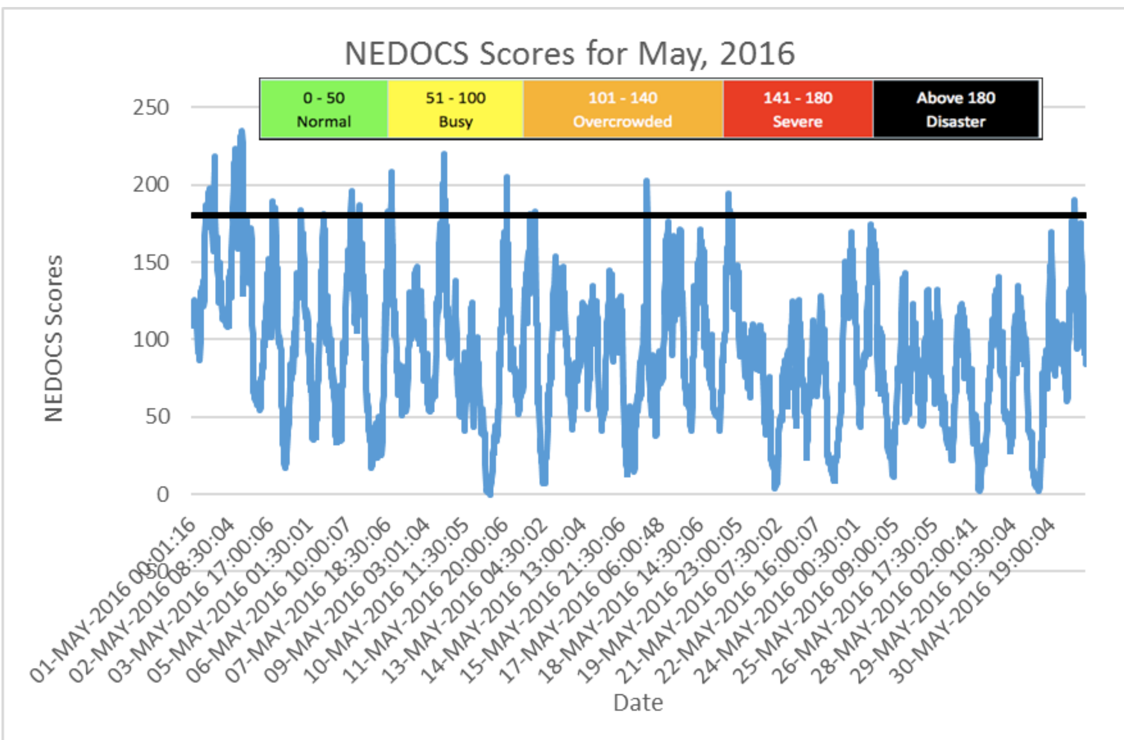

Figure 5: NEDOCS scores for May 2016

To normalize the NEDOCS scores, we divide each NEDOCS score by the historical maximum score of 310 to give the functionality lost at time t. See Equation 6.

$$Functionality = 1 - \frac{NEDOCS\ Score}{Historical\ Max\ NEDOCS\ Score}$$

Equation 6

This indicates that if the NEDOCS score is 180, for example, then the functionality lost would be 180/310 = 0.5806, which would then be subtracted from 1 to get the remaining functionality. This remaining functionality value is then plotted over time, as shown in Figure 6 for the data collected on May 2.

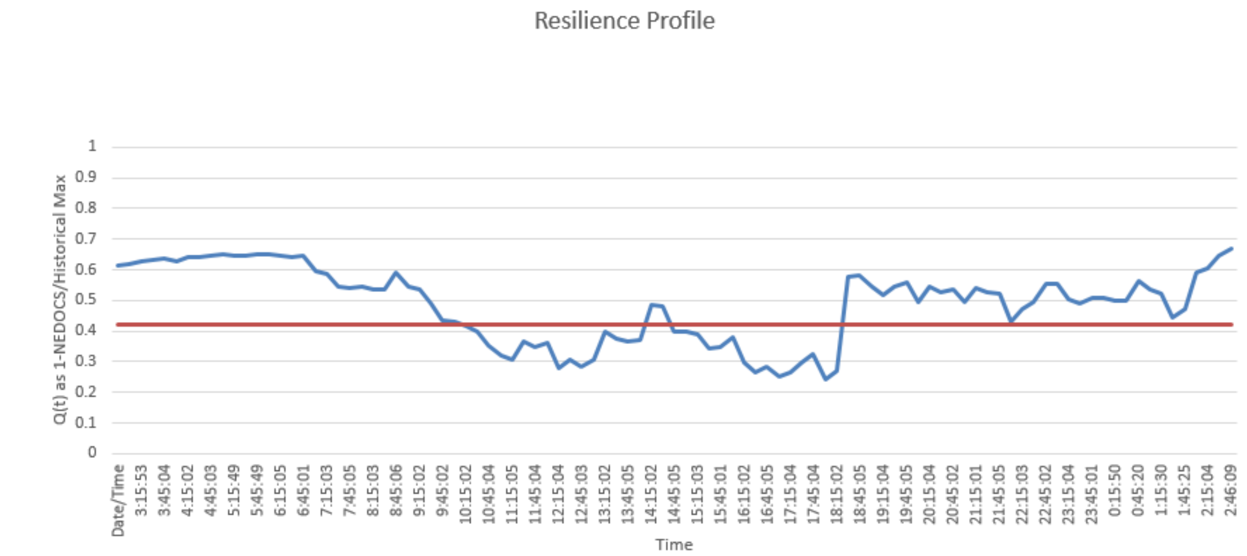

Figure 6: Resilience profile for May 2

The horizontal line in Figure 6 represents the disaster threshold, the point at which the system is experiencing disaster level overcrowding. For the 31 days of data collected, a T* value of 8 hours is sufficient to cover the longest disaster event to occur in a given day. The data to calculate the NEDOCS score is collected every 15 minutes, which provides us with 32 data points in each T* interval of 8 hours to calculate the resilience. The area calculated is that which falls below the minimum value between the functionality curve and the disaster threshold. If the functionality curve exceeds the threshold, that value defaults to a threshold value of 0.4194 to account for moments when the NEDOCS score temporarily returns above the disaster threshold and then returns to disaster level. We then find the ratio of the sum of the calculated areas and the area had there been no disaster.

For example, during a period of time in which disaster level overcrowding did not occur, the area below the threshold is 0.4194, multiplied by the number of data points, 32, which equals 13.4208. Therefore, if disaster level overcrowding does not occur in a time period, the total area below the threshold is 13.4208, which provides the denominator for our resilience calculation. To gain the numerator for our equation we examine the data from May 1, a date when disaster level overcrowding did occur. To begin, we sum the area under the functionality curve and obtain the value 12.769. We find the ratio of the area under the functionality curve and the total area under the threshold to be 12.7699/13.4208 = 0.9515. This provides us with a relative resilience value in which to relate to the other resilience values on other days of disaster level overcrowding.

In assessing the multidimensionality of the data, we recognize that the variables $\mathbf{b_{ED}(t)}$, number of total ED beds, and $\mathbf{b_{h}(t)}$, total number of occupied and vacant inpatient beds in the hospital, remain constant in this time period; however, the other variables fluctuate in accordance with the disaster level overcrowding events. We analyze each of these variables with respect to disaster level NEDOCS scores to determine the relative component resiliencies during each period of disaster level overcrowding. As an example, the component $\mathbf{L_{ED}(t)}$, total number of patients in the ED that are occupying beds, including hallway beds, is analyzed in Figure 7.

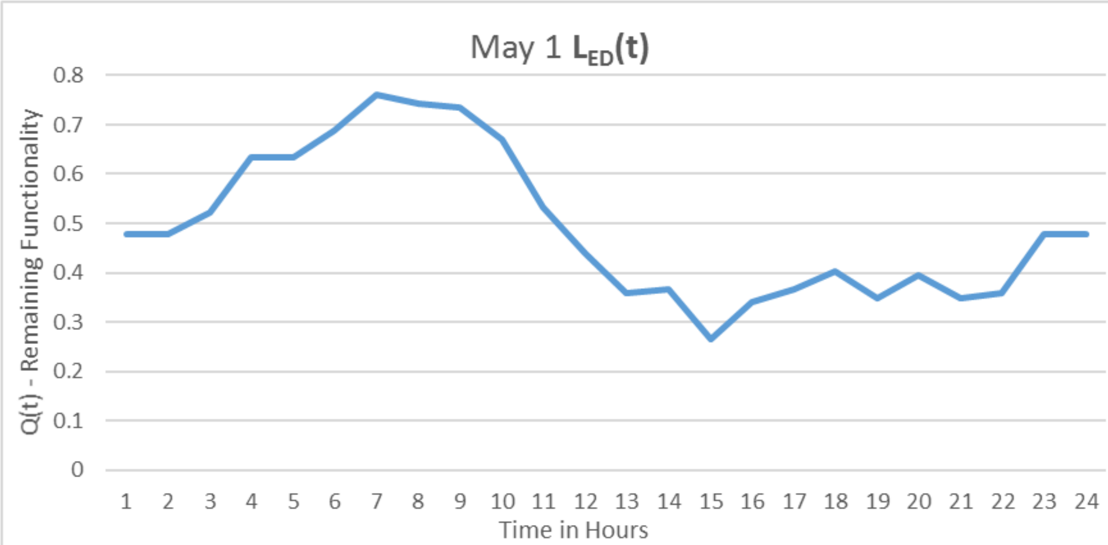

Figure 7: Example of component resilience

In Figure 7, the time period during which the ED is experiencing disaster level overcrowding is from hours 12 through 20. The historical max **L_{ED}(t)** is 109, which provides us with the denominator for our equation. We calculate the system's remaining component functionality with respect to **L_{ED}(t)** by the following equation (See Equation 7).

$$Component\ Functionality = 1 - \frac{L_{ED}(t)}{Historical\ Max\ L_{ED}(t)}$$

Equation 7

From the results of this calculation we graph the loss of component functionality over time and develop a threshold to determine the component predicted resilience. The lowest number of patients in the ED during a disaster level overcrowding event is 60, which provides us with the numerator for the above equation. With this data, we are able to calculate that any component functionality reading below 0.4495 is below the disaster threshold. Likewise, we calculate the resilience by finding the sum of the area below the curve and the area associated with T*, just as we did for the overall resilience. We perform the same algorithm with each of the components to find each dimension's component resilience value.

After calculating each component resilience value, we examine the effect of each component on the overall resilience. In order to assess this, we utilize latent variable analysis. The true overall resilience of the emergency department is the latent variable, and the calculated overall resilience, R, is the indicator variable. The latent variable of true overall resistance is calculated using the count-based measures of component resiliencies $\mathbf{r_{LED}}$ and $\mathbf{r_{Lrp}}$. We then use partial least squares regression to regress (see Equation 8):

$$Overall\ Resilience = Overall\ Recoverability\beta_1 + Overall\ Resistance\ \beta_2$$

Equation 8

We depict this visually as follows (See Figure 8):

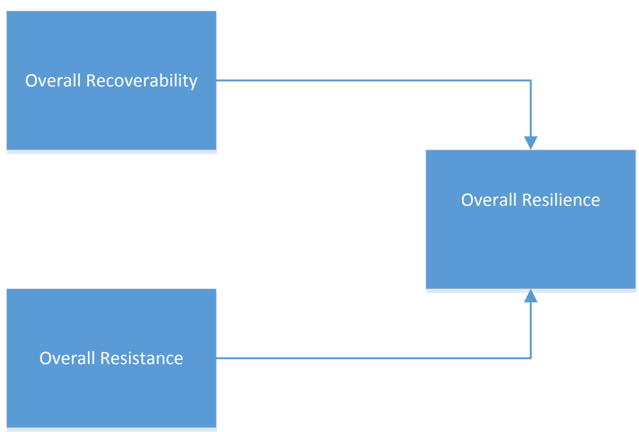

Figure 8 Primary Regression

The indicator regressions are then performed as follows (See Equation 9 and 10):

$$Overall\ Resistance = \beta_1 r_{L_{ED}} + \beta_2 r_{L_{rp}}$$

Equation 9

$$Overall\ Recoverability$$

$$= \beta_1 r_{L_{admit}} + \beta_2 r_{W_{ED}} + \beta_3 r_{W_{admit}} + \beta_4 (r_{L_{admit}} * r_{W_{ED}}) + \beta_5 (r_{L_{admit}} * r_{W_{admit}})$$

$$+ \beta_1 (r_{W_{ED}} * r_{W_{admit}}) + \beta_1 (r_{L_{admit}} * r_{W_{ED}} * r_{W_{admit}})$$

Equation 10

Using the above equations, we calculate the overall resilience and present our results in the following section.

4. Results and Summary

We begin our calculations by determining the predicted resilience for each day that experienced disaster level overcrowding, followed by the resilience of each of the components (See Table 1).

Date of Disaster Level Event	Overall Predicted Resilience	Component Predicted Resilience				
	R	**r LED**	**r Ladmit**	**r Lrp**	**r WED**	**r Wadmit**
5/1/2016	0.9515	0.6893	0.7089	0.6931	0.8911	0.7077
5/2/2016	0.8060	0.7664	0.7511	0.7434	0.8827	0.7390
5/3/2016	0.9952	0.7392	0.8889	0.7831	0.9580	0.9673
5/4/2016	0.9987	0.9728	0.9867	0.9788	0.9805	0.9908
5/5/2016	0.9999	0.9955	0.9600	0.9418	0.9999	0.9462
5/6/2016	0.9537	0.4887	0.6733	0.5026	0.8242	0.8039
5/7/2016	0.9813	0.7755	0.9511	0.6296	0.9630	0.9576
5/9/2016	0.9714	0.7438	0.7956	0.8466	0.9554	0.9332
5/11/2016	0.9921	0.9388	0.9378	0.9365	0.9924	0.9833
5/12/2016	0.9676	0.5782	0.8667	0.7037	0.9444	0.9132
5/16/2016	0.9603	0.9615	0.9600	0.9630	0.9894	0.9787
5/19/2016	0.9644	0.7506	0.7067	0.9471	0.9409	0.8030
5/31/2016	0.9976	0.9111	0.9467	0.9630	0.9812	0.9620

Table 1: Predicted resilience for days with disaster level overcrowding

Walking through our data illustrates how our system can be used to analyze and compare situations of low resilience. We can see in Table 1 that the days of lowest resilience for the subject ED were May 1 and May 2. These two days were also the only days on which the ED exhibited severely low resilience to the components of $\mathbf{r}_{\mathbf{WED}}$ and $\mathbf{r}_{\mathbf{Wadmit}}$. Both of these values have to do with delays in throughputs, which significantly affect system recoverability. Based on our analysis, decreasing throughput times would have the most impact on decreasing the magnitude of the disaster level-overcrowding events occurring on May 1 and 2. Throughputs are associated with the variables of $\mathbf{r}_{\mathbf{Ladmit}}$, $\mathbf{r}_{\mathbf{Wadmit}}$ and $\mathbf{r}_{\mathbf{WED}}$, which concern the amount of time it takes for a patient to be transferred from the door of the emergency department to the ED bed and the time it takes for a patient to be transferred from the ED bed to an inpatient bed. These throughput values affect patient waiting time and reflect a staff that is under pressure to triage and care for patients until they can be placed in the correct locations. However, May 1 and May 2 notwithstanding, on the other days on which disaster level overcrowding events occurred, $\mathbf{r}_{\mathbf{LED}}$ and $\mathbf{r}_{\mathbf{Lrp}}$ were the most significant challenges to resilience. Both $\mathbf{r}_{\mathbf{LED}}$ and $\mathbf{r}_{\mathbf{Lrp}}$ relate to the volume and type of patients presenting to the emergency department. These components indicate a patient surge, which placed strain on the available resources, thus reducing the resilience of the system. As the number of critical care patients in the ED ($\mathbf{r}_{\mathbf{Lrp}}$) increases during a surge, more demand is placed on staff due to the increased complexity of the patient care required. As the nurse to patient ratio moves from the 1:3, 4, or 5 ratio used for average ED patients to the 1:1 or 1:2 ratios used with critical care patients, fewer staff members are available to provide care, thus decreasing the resilience of the system.

The comparison and analysis demonstrated above illustrate how our model can be used to compare situations where the resilience is the lowest and implement interventions aimed at the resistance components, the recoverability components or both. In the case of our subject ED during the study period, the two lowest resilience values on May 1 and May 2 indicate that the recoverability components is affected. Given this information, decisions could be made to improve the throughput times, thus decreasing the magnitude of resilience lost. However, the remaining disaster level overcrowding events during the study period were caused by volume and limited staffing, which represent situations where the resistance components are affected. In this resistance deficiency situation, adding more room for additional patients and increasing staff to account for critical care patients would ameliorate the effects of overcrowding. Over time, the analyses modeled here would reveal larger patterns, enabling decision makers to compare different situations. In the long term, the facility could use this information to determine whether to make efforts to decrease the magnitude of disaster events or to decrease how often disasters occur.

Our model can be further analyzed to determine how effective various interventions might be in mitigating disaster level overcrowding. Utilizing the overall predicted resilience and the component resiliencies, we assess the model with partial least squares (PLS) regression. The regression results are shown in Figure 9:

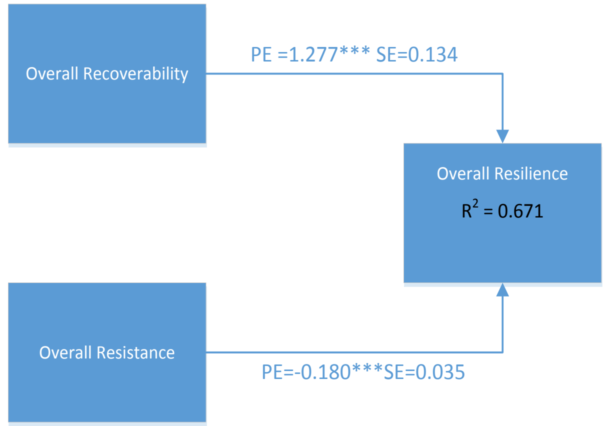

*Figure 9: PLS regression, PE = parameter estimate, SE = standard error, p<.01 = ****

In Figure 8, the R^2 value of 0.67 indicates that 67% of the overall resilience is accounted for by the latent variables of overall recoverability and overall resistance. Examining the parameter estimates, we see that that overall recoverability has a significantly higher magnitude than overall resistance. In our subject ED, then, manipulating the underlying variables associated with overall recoverability would improve the resilience by a factor of almost 7. Along with the component resilience, the PLS regression could also be used by the facility to make long-term improvements to ED resilience.

To further facilitate such decisions, we analyze how the indicator variables affect each latent variable of overall resistance and overall recoverability. These parameter estimates are found in Table 2.

Indicator Variable	Parameter Estimate	Standard Error	Latent Variable
r_{LED}	1		Overall Resistance
r_{Lrp}	0.851	0.035	Overall Resistance
r_{Ladmit}	1		Overall Recoverability
r_{Wadmit}	1.944	0.084	Overall Recoverability
r_{WED}	2.555	0.097	Overall Recoverability
$r_{WED} * r_{Wadmit}$	2.736	0.103	Overall Recoverability
$r_{Ladmit} * r_{Wadmit}$	3.289	0.118	Overall Recoverability
$r_{Ladmit} * r_{WED}$	3.982	0.138	Overall Recoverability
$r_{Ladmit} * r_{WED} * r_{Wadmit}$	4.566	0.153	Overall Recoverability

Table 2: Indicator variables parameter estimates, p<0.01 for all variables, rLED and rWED are fixed to 1, no significant interaction between rLED and rLrp

We interpret the indicator variables to examine the parameter estimates under each latent variable and examine how the magnitudes of the parameter estimates relate to each other. For overall resistance, the variable $\mathbf{r_{LED}}$ is fixed to 1 and the parameter estimate for $\mathbf{r_{Lrp}}$ is then found to be 0.821. The parameter estimate for $\mathbf{r_{LED}}$ is higher than the parameter estimate for $\mathbf{r_{Lrp}}$, suggesting that improvements to $\mathbf{r_{LED}}$ would have more impact than improvements to $\mathbf{r_{Lrp}}$ on improving the overall resistance of the system. Each parameter estimate provides the return on investment for improving the associated component resilience.

Overall recoverability cannot be analyzed the same way due to the interaction effects between the three components. The variable $\mathbf{r_{Ladmit}}$ is fixed to 1, and the parameter estimates for the accompanying variables of $\mathbf{r_{WED}}$ and $\mathbf{r_{Wadmit}}$ are found to be 2.555 and 1.994 respectively. Since there is a three-way interaction between each of the indicator variables, we must examine the relevance of the interaction using the simple slopes t test, shown in Figure 10.

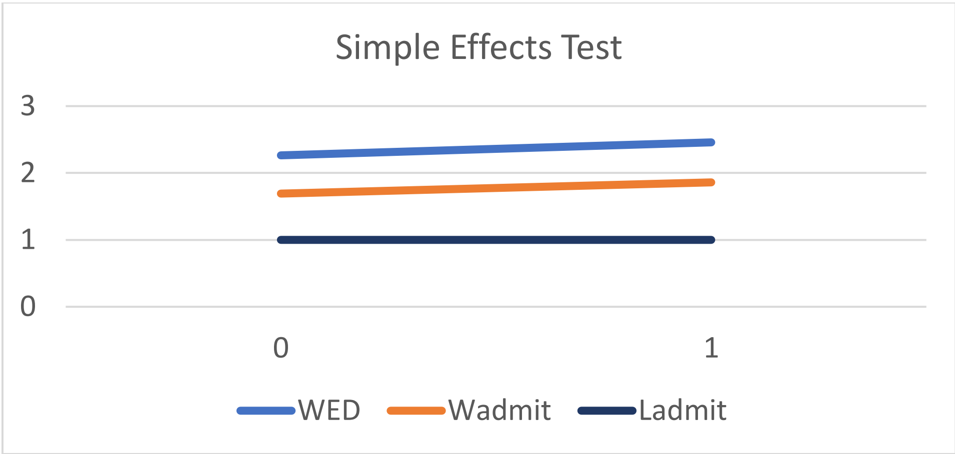

Figure 10: Simple slopes analysis of component resilience effects on overall recoverability

From Figure 10, we hold the r_{Ladmit} variable to 1 and examine the interactions of r_{WED} and r_{wadmit}. We can see that the means for the two throughput associated component level resiliencies are both increasing and that the magnitude of the r_{WED} is higher than the magnitude for r_{Wadmit}. This finding indicates that in this particular analysis, the throughput improvement associated with moving patients from triage to an ED bed has the greatest effect on the overall recoverability of the system.

We continue the analysis on overall recoverability, identifying that decreasing the amount of time patients are waiting for transfer to an ED bed will have the greatest impact on improving the overall recoverability. The next most impactful factor is identified as decreasing the throughput times in transferring ED patients to inpatient beds. Based on the main effects, we also identify the factor with the least return on investment in improving overall recoverability, which is $\mathbf{r_{Ladmit}}$, or the number of patients waiting to be transferred to an inpatient bed. However, since each main effect and interaction effect shows a positive association with the latent variable overall recoverability, adjusting any or all of the indicator variables will improve overall recoverability in a disaster event.

In order to assess the fit indices of the PLS regression, we examine the indices in Table 3:

Fit Indices	Log-likelihood	AIC	BIC	X^2	SRMR
Value	3793.434	-5192.418	-5136.701	2350.451	0.028

Table 3: PLSPM Model Fit indices

We supply the fit indices in Table 3 with the log-likelihood, AIC and BIC, available for future research to make comparisons and the chi square and SRMR (Standardized Root Mean Square Residual) as indicators of the fit of our model. The chi square statistic is 2350.451 and the SRMR is 0.028. Based on Hu and Bentler (1999), an SRMR of less than 0.08 is an indication of good model fit.

4.1 Predictive Model

Following the identification of the factors impacting ED resilience to disaster level overcrowding events, we seek to create a model that may be able to predict disaster level overcrowding. Using RStudio, we develop a general linear model in order to perform logistic regression and develop a binary classifier. As inputs, we use the NEDOCS data from our original data set. The goal of the model is to determine if a disaster level overcrowding event is imminent in the next six hours. We utilize the data of each of the NEDOCS score component, recorded on an hourly basis. The data is manually tagged with a ‘1’ if the recorded data was within six hours of a disaster level overcrowding event and a ‘0’ if the data is not within six hours of disaster level overcrowding. Data recorded during disaster level overcrowding is removed from the data set, as it has no bearing on the ability to predict the event. After we tag the data, we split it into two groups: 90% of the data is used to train the model and 10% is used to test the model’s predictive ability. The glm function is used for model fitting. See Table 4.

	Est.	SE
Intercept	-4.471***	0.547
b_{ED}	NA	NA
b_h	NA	NA
L_{ED}	0.004	0.009
L_{admit}	0.028	0.024
L_{rp}	0.282***	0.06
W_{ED}	-0.136	0.13
W_{admit}	0.055*	0.022

Table 4: Regression parameter estimates and standard error

Next we select a time period for our calculations. The vice president of emergency services at Carilion Clinic identified six hours as the necessary amount of time to make adjustments to potentially prevent or mitigate a disaster event, and therefore we use that time period.

We can then analyze the fit and interpret the results from the model. First, we see that $\mathbf{b_{ED}}$ and $\mathbf{b_h}$ were not defined because the total number of beds in the ED and the total number of inpatient beds did not change in the time period examined. Next, we see that the only significant values in the model are $\mathbf{L_{rp}}$, the number of critical care patients, and $\mathbf{W_{admit}}$, the longest boarding time of patients in the ED. Thus, we see that the number of critical care patients is the strongest predictor of whether a disaster level overcrowding event is imminent within six hours, and the longest boarding time in the ED is the next strongest predictor. To further analyze the fit of the model, we examine the table of deviances. See Table 5.

	Residual Deviance	Deviance
null		445.09
b_{ED}	0	445.09
b_h	0	445.09
L_{ED}	9.2287**	435.86
L_{admit}	5.555*	430.3
L_{rp}	22.172***	408.13
W_{ED}	0.988	407.14
W_{admit}	5.61*	401.52

Table 5: Deviances

As we add variables into the null model, the analysis shows how the model improves. The larger the residual deviance value, the more explanation that variable provides regarding the model fit. From this analysis, we see again that $\mathbf{L_{rp}}$, the number of critical care patients, has the most influence on the model. Finally, we utilize the McFadden R^2 index to assess model fit. For this model, the R^2 is 0.098, indicating that about 10% of the variability in this model can be explained.

To assess the predictive power of the model, we utilize the remaining 10% of the data as test data. We use a threshold value of 0.111, which was the cutoff value that provided the best balance between the false positive rate and the false negative rate, to simplify – it minimizes the number of mistakes we are making. We find that our model has a 74.2% accuracy in predicting whether disaster level overcrowding is imminent within six hours. However, the model's accuracy is dependent on how the data was split. The receiver operating characteristic (ROC) curve is used to visualize and quantify the diagnostic ability of a binary classifier as the threshold is varied (Griner et al, 1981). The true positive rate represents the sensitivity of our model and the false positive rate represents the specificity of our model. To provide a better performance metric, we analyze the ROC curve. See Figure 11.

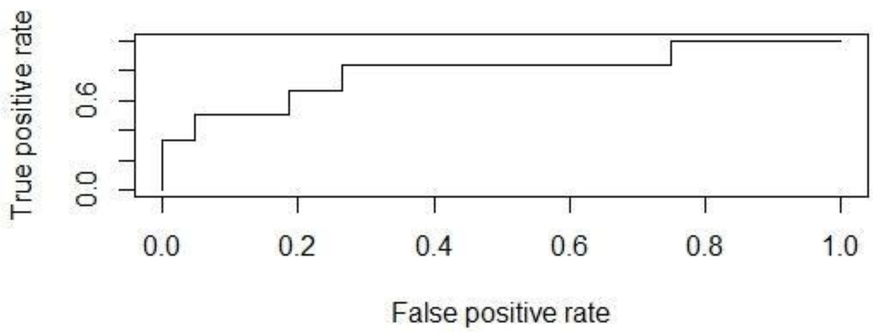

Figure 11: ROC curve

The area under the curve (AUC) is equal to the probability that our classifier will rank a positive instance higher than a negative instance (Fawcett, 2006). We find the (AUC) is 0.79 for our model and provides a means for comparisons to other models.

5. Discussion

To begin the discussion, we revisit the original NEDOCS equation to compare the predicted impact of each coefficient with the findings of our study. See the original NEDOCS equation below (See Equation 11):

$$NEDOCS(t) = -20 + 85.5\left(\frac{L_{ED}(t)}{b_{ED}(t)}\right) + 600\left(\frac{L_{admit}(t)}{b_h(t)}\right) + 5.64W_{ED}(t) + 0.93W_{admit}(t) + 13.4L_{rp}(t)$$

Equation 11

Two of the variables, $b_{ED}(t) = 72 \text{ and } b_h(t) = 532,$ are constants. Reworking the equation, accounting for the constants, the new coefficient for the number of patients in the ED is 1.18 $\mathbf{L_{ED}(t)}$ and the number of patients waiting on an inpatient bed is 1.12 $\mathbf{L_{admit}(t)}$. Based on the NEDOCS equation's coefficients, it should follow that $\mathbf{L_{rp}(t)}$, the number of critical care patients, has the highest coefficient and should have the greatest impact on the NEDOCS score. It should also follow that $\mathbf{W_{admit}(t)}$, the longest boarding time of patients in the ED waiting to be admitted to the hospital, has the smallest coefficient and should have the least effect on the NEDOCS score. In fact, however, we find quite the opposite: the resilience to the number of critical care patients $\mathbf{r_{Lrp}}$ had the smallest coefficient, indicating that, in terms of resilience to disaster level overcrowding, the number of critical care patients is not as impactful as expected. However, $\mathbf{r_{WED}}$, the resilience to the waiting time from triage to ED bed placement, has the highest coefficient, indicating that decreasing the time from patient admission to an ED bed will have the most impact on the overall resilience.

It is worth noting that when predicting disaster level overcrowding rather than analyzing it, $\mathbf{L_{rp}}$ has the greatest influence, which is commensurate with the weights in the NEDOCS equation. We can see, then, that decision makers facing a predicted overcrowding event will, theoretically, make different choices than those who are already in the middle of an overcrowding scenario.

6. Conclusions

6.1 Theoretical Implications

The key research question addressed in this study was: "How can resilience be quantitatively measured in the emergency department and what decisions can be made by administration to improve this resilience?" Although overcrowding has been assessed in the extant literature, no study has hitherto examined resilience to such disaster events. To investigate these issues, we assess the resilience of an emergency department across 13 disaster level overcrowding events. Our study extends previous work on predicted resilience, multidimensionality and the hierarchal structure of resilience, and captures new aspects of system resilience by examining its component resiliencies.

We believe that this novel concept of component resilience makes a significant theoretical contribution to the field. Our component resilience model builds on existing work to capture dimensions of the overall recoverability and overall resistance of the system at a more granular level. Assessing resilience at this granular level allows decision makers to pinpoint which components of the system should be improved to increase resilience to disaster level overcrowding. Although previous models have contributed to our understanding of the ED as a system, our model allows a decision maker to adjust multiple parameters of the dimensions of resistance and recoverability to meet the immediate needs of the ED and provide justification for the decisions being made, thus addressing both quality of care and associated costs.

Our study also builds on the existing literature by extending the theory of multidimensional disaster resilience to conceptualize resilience from an abstract perspective. To extend and expand the theory of multidimensional resilience, we develop the idea of component resilience, identify relevant components, and determine how these components relate to the overall system resilience. The theory of component resilience allows for modification of how overall resilience is examined and studied when seeking mitigating factors.

6.2 Practical Implications

The key practical contribution of our study is that we provide the Carilion Clinic's hospital administration with a decision support process to improve the resilience of its emergency department to disaster level overcrowding. ED overcrowding is often attributed to patient surge, but using our model, an administrator can calculate the overall resilience to several disaster events, examine the component level resiliencies for their particular ED, and determine what changes would have the greatest impact on improving the overall resilience. Some changes are more feasible than others (for instance, adding more staff takes less time than adding additional beds), but the ability to identify which factor is having the greatest impact on overcrowding can assist in making the appropriate decision. For example, if decreased resilience is found to be a result of the total number ED patients, and if that is found to be the primary factor identified across several disaster events, it is clear that more space needs to be allocated to the emergency department. As another example, if the loss in resilience is due to the throughput time from triage to an Emergency Department bed, then hospital administrators could add additional staff members whose job is to focus on reducing throughput times. And as a final example, if the loss in resilience is due to the volume of critical care patients, then increases in both staff and in specialized supplies may be necessary. The intervention can be specifically matched to the situation to minimize change and inconvenience, as opposed to the current generic response of making changes in all areas. This also decreases costs in both the short-term and long-term by identifying when the most costly changes, such as adding more ED space, would truly be cost effective and appropriate.

Our secondary research question was, “Do factors exist that can be evaluated to predict a disaster level overcrowding event before it occurs?” Using our model, which is designed to predict an imminent disaster level event within six hours, administrators could determine whether a disaster event is likely in the near future and implement measures aimed at preventing or mitigating the effects of the overcrowding event. Such proactive action would reduce associated costs and minimize the impact of overcrowding in the ED and in the hospital as a whole.

Lastly, our work can be applied to settings beyond the emergency department. Within the hospital setting, operating rooms have similar overcrowding issues that can be analyzed using resilience analyses, and improvements could be made utilizing a similar component resilience framework. Other potential applications lie in fields beyond healthcare. This generalizability breaks new ground for systems resilience research originating in a healthcare context. Previously, such work was not generalizable, but the idea of component resilience makes our framework and models flexible and adaptable enough to benefit research and practice in other fields of study.

7. Future Work and Limitations

Based on the findings and outcomes of this study, we identify several areas for future research. As previously mentioned, our framework can be replicated and applied to other areas of the hospital, such as the operating room. And since our approach is also generalizable, its predictive power and granularity may become an asset to decision makers in other industries outside of healthcare.

Several limitations exist in our study, and these limitations also suggest opportunities for future research. For instance, we only collected data for one month, so future research could include data from multiple months and different months of the year to minimize schedule trend biases. Also, we only looked at data from one large academic medical center, so future research could determine whether the factors are the same at other types and sizes of hospitals and examine component resilience across multiple emergency departments. Our model was able to explain 67% of the variability in the resilience of this system; however, future research may identify the other contributing factors.

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Chapter 3: Assessing Usability in the Inpatient Setting: Survey and Empirical Analysis

1.0 Introduction

Several laws mandate that healthcare institutions use electronic health record (hereafter, EHR)[3] systems. These include the Health Information Technology for Economic and Clinical Health (HITECH) Act[4] and portions of the Affordable Care Act (ACA) [5], both of which share the common goal of making healthcare more affordable and efficient. The HITECH meaningful use standards, along with the standards of the ACA's Medicare shared savings program, require all private and public healthcare institutions in the United States (US) use EHRs to protect the privacy and security of patient data or else be subject to monetary penalties and legal action (U.S. Department of Health and Human Services, 2009; Centers for Medicare and Medicaid Services, 2016; Mostashari, 2013; Centers for Medicare and Medicaid Services, 2015). Under the ACA, non-compliance with these requirements will reduce Medicare reimbursements from the US government (U.S. Department of Health and Human Services, 2010). Another aspect of the ACA requires hospitals to adhere to evidence based standards of care, which require documentation in the EHR to ensure the hospital receives reimbursement for care provided (Barjis, Kolfschoten and Maritz, 2013; Huerta, Thompson, Ford and Ford, 2013; Tremblay, Deckard, and Klein, 2016; Smith, Bradley, Bichescu, and Tremblay, 2013; Kwon and Johnson,

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[3] EHRs are often confused with electronic medical record systems (EMRs). According to the National Coordinator of Health Information Technology an EMR is simply a digital version of a paper chart that is confined within a single hospital system, whereas an EHR is built to share information with other healthcare providers and beyond a single hospital.
[4] The HITECH Act was created to expedite the promotion and use of health information technologies. The privacy and security of health information are addressed in Subtitle D of the HITECH Act that improves several provisions in the existing healthcare laws.
[5] The ACA requires hospitals and primary care physicians to change practices by incorporating technology into their methods of care to improve patients' health outcomes, lower costs, and increase accessibility and availability of healthcare to all citizens.

2013). Although many healthcare institutions had already adopted EHRs before the passage of HITECH and ACA, these formal policies added a great deal of pressure on a system already strained by technology use.

Adaptation of EHR usability has become one of the most prominent requirements as healthcare information systems progress past their implementation phase. Hospital staff have limited time to document their work as they focus on caring for the patients, who remain their utmost priority, and improvements to EHR usability would improve the workload of staff and allow them more time to devote to patient care. In departments operating under high stress, such as the emergency department, EHRs have been controversial in their contribution to the medical field (Ben-Assuli and Leshno, 2013). Prior research (e.g., Poissant, Pereira, Tamblyn and Kawasumi, 2005) has found that healthcare personnel have difficulty completing their documentation at the time of care, which forces them to delay documenting, sometimes until after their shift has ended. Nearly a decade later, a 2014 survey of 14,000 nurses indicated that nurses were still dissatisfied with their EHRs and that documentation takes away from patient care, with many nurses documenting long after the care was given (Perna, 2014; Windle, 2017). In the health service industry, a delay in documentation can lead to medical errors; therefore, usability is also important regarding patient safety. This clearly indicates that there is a need for quality improvement in the healthcare industry regarding EHR use (Field, Heineke, Langabeer and DelliFraine, 2014).

The aim of this paper is to examine factors influencing managerial decision making when adapting the EHR to clinical staff use in the continued use phase. We analyze survey results from 509 healthcare workers, 86% of whom are nurses, and establish an overarching framework built on information systems theories to identify the EHR's strengths and weaknesses from a usability standpoint. Using a mixed-methods approach to data analysis, as suggested by both Choi, Cheng, and Zhao (2016) and Venkatesh, Brown, and Bala (2013), we use both quantitative and qualitative measures. Mixed methods allows us to frame a theoretical model, assess with academic rigor, and then follow up with text analysis to explain why phenomenon in our findings occur. Examination of comments made by staff identifies modifications that managers could implement to improve EHR adaptation to continued use behavior.

From a theoretical standpoint, using the theory of reasoned action, we identify significant determinants of usability, adaptation, and fit in the healthcare setting, and we also propose additional constructs that will contribute to the extant literature (Fishbein and Ajzen, 1975). In particular, we fill a research gap regarding conceptualization of individual feature use on adaptation of information systems use outcomes. Our research framework identifies new constructs, i.e., *perceived information security* and *user engagement*, that enhance the impact of adaptation on continued use behavior. We also question the application of previous definitions of *social influence* and provide a new adaptation to meet the needs of information systems in the continued use phase.

Our contributions to practice come from recommendations for managerial decision making related to discovering healthcare worker motivations associated with usability, and they include identifying important insights from analysis of the text responses that explain some addressable, albeit major, usability complications. Analysis of the comment sections of the administered survey revealed several areas of usage deficiencies that provide a platform for managerial decisions promoting staff education and future usability adjustments. In particular, streamlining the flowsheets and analyzing the workflow and documentation needs allow the recognition of pertinent aspects and removal of superfluous areas. Overall, our findings offer important insights regarding EHR adaptation to improve EHR usability, reduce strain on staff time, and improve safety features.

The organization of the rest of the paper is as follows. We first provide a theoretical foundation that examines existent theoretical information systems use and adaptation models. Next, we introduce our model as it applies to our analysis and we propose our hypotheses. We then discuss our methods, results, and provide data analysis. Last, we present our limitations, suggestions for future research, and conclusions.

2.0 Theoretical Foundation

The underpinning theory of the majority of use and adoption streams in the literature stems from the Theory of Reasoned Action (Fishbein and Ajzen, 1975), which attempts to understand the behavioral intention toward a particular action based on an individual's attitude and beliefs. Overall, many streams of literature exist within the information systems literature related to how information systems are used building on concepts of the theory of reasoned action. We first discuss streams of literature on the acceptance of new implementations of information. Then we discuss streams of literature on the success of an implemented information system. Next, we discuss streams of literature on post adoption phenomena, adaptation, and use continuance theories. Finally, we discuss our research gap and propose an approach to fill this gap.

There is a significant amount of existing literature discussing adoption and acceptance models. The original paper on the Unified Theory of Acceptance and Use of Technology

(UTAUT) and the many extensions to UTAUT provide a complete history of adoption and acceptance models until 2014 (Venkatesh, Morris, Davis and Davis 2003; Venkatesh, Thong and Xu, 2016). More recently, a multi-level framework of technology acceptance was introduced that examines higher-level contextual factors as well as individual level contextual factors. The main effects of the original UTAUT and UTAUT2 models are included in this effort, and the main constructs of the new framework include the constructs: *facilitating conditions* – that refer to "user perceptions of the resources and support available to perform a behavior"; *individual beliefs* – that include "performance expectancy, effort expectancy, social influence, hedonic motivation, and price value that influence behavioral intention"; *habit* – "a perceptual construct that reflects the results of prior experiences"; and *behavioral intention* – behaviors associated with intention to use a technology (Venkatesh, Thong and Xu, 2012; Venkatesh, Thong and Xu, 2016).

The information systems success model examines implementation to determine success based on independent variables of: *system quality*, *information quality*, *use*, *user satisfaction*, *individual impact*, and *organizational impact* (DeLone and McLean, 2003; Petter, DeLone and McLean, 2013). The *system quality* construct, "defined as desirable characteristics of an information system", is most relevant to our study as it includes the concepts of ease of use and system flexibility (DeLone and McLean, 1992). Due to healthcare regulations mentioned in the introduction, success is more of an expectation than in the past and, at this time, EHRs have progressed into the adaptation phase as they continue to reach for the optimal success goal. In addition, because our study focuses on adaptation instead of acceptance and adoption, these studies can provide a basis for the overall research effort but other models better serve as a foundation for our specific study.

After the adoption phase of a new information system, the organization enters the continued use phase. There is a unique organizational context when examining healthcare information systems models as the healthcare industry is the only industry mandated by the federal government to use an information system. Several studies have noted that different factors affect potential adopters of new information systems, as opposed to continued users of current information systems (Karahanna, Straub and Chervany, 1999; Agarwal and Prasad, 1997). Many models, including those of adoption and success, are insufficient in testing use and usability within the organizational context of the healthcare setting during this continued use phase.

Specific factors in the streams of literature associated with technology acceptance may need to be adjusted in the continued use phase, such as the modification of the *behavioral intention* construct to behavioral *habit* (de Guinea and Markus, 2009). Other research also has studied constructs in a longitudinal study to determine their value in post-adoption phenomena (Kim and Malhotra, 2005). This particular study concluded that perceived ease of use in the post-adoption phase, "the degree to which a person believes that using a particular system would be free of effort", is a significant factor in the continued use of an information system (Kim and Malhotra, 2005).

Adaptation is the assimilation and accommodation of new knowledge (Piaget, 2001). Information systems adaptability comprises supportive and informational social networks and social influences within the company (Bruque, Moyano, and Eisenberg, 2008). Additional major predictors of a system’s adaptation are the relative advantage, cost, and technical compatibility, such as ease of use (Premkumar, Ramamurthy, and Nilakanta, 1994). Many security requirements also force individuals to adapt their work routines due to password requirements and constant logging on and off at terminals (D'Arcy, Herath and Shoss, 2014). Representational fidelity and developing new features during the continued use of existing features allows adaptation through system exploration and integration into the work routine (Liang, Peng, Xue, Guo and Wang, 2015).

We seek to fill the research gap in the direction of conceptual technology use at the feature use level and the linkage to individual outcomes discovered in recent literature (Venkatesh, Thong and Xu, 2016). Our aim is to augment findings of other studies that have determined health information systems to be trustworthy and useful (Hung, Tsai and Chuang, 2014). There are several factors for exploration when assessing an information system in the continued use phase. Perceived ease of use, identified as prevalent in adoption models, is still an important element in the continued use phase. *Social influence* is “the degree to which an individual perceives that it is important that others believe he or she should use the new system” (Venkatesh and Davis, 2000; Venkatesh et al., 2003), as an element of informational support is crucial to adapting an information system but needs a new operationalization during the continued use phase. Our goal is to understand how these constructs influence feature use and adaptation in information systems.

3.0 Research Model and Hypotheses

We now describe our conceptual model and develop our hypotheses. Three main constructs: *user engagement, perceived information security,* and *perceived ease of use* describe the likelihood that a user will implement a new feature into their current workflow. A fourth main construct, *social influence*, examines how users' influence changes the adaptation of the information system to improve use. The second level construct, *feature use*, determines if a new feature is being utilized, and combined with *social influence* it gauges how an information system is adapting to fit a specific organizational context, as the information system reaches for success. We call this *affirmative system adaptation*. Table 6 provides definitions for each of these constructs, and this leads to our conceptual model given in Figure 12.

Construct	**Definition**	**Examples of measures**
Social Influence	Individual user influence on changes to an information system	User input on how the system is used, access and communication
Perceived Information Security	Adequate security, continuity, safety and protection of users and users' information	Signing in and out features; safe information transmission; safe verification of information
Perceived Ease of Use	The ease in which an information system can be used	Accessibility of information; presentation of information; ease of finding information
User engagement	Individual users' representation and motivation	The user has representation in changes; the user is motivated to stay informed of changes
Feature Use	The actual use of features in the Information system	Individual features available in the information system
Affirmative system adaptation	The ability and progress an information has in adapting to changes	Adaptions that indicate changes to meet users' needs

Table 6 Construct Definition

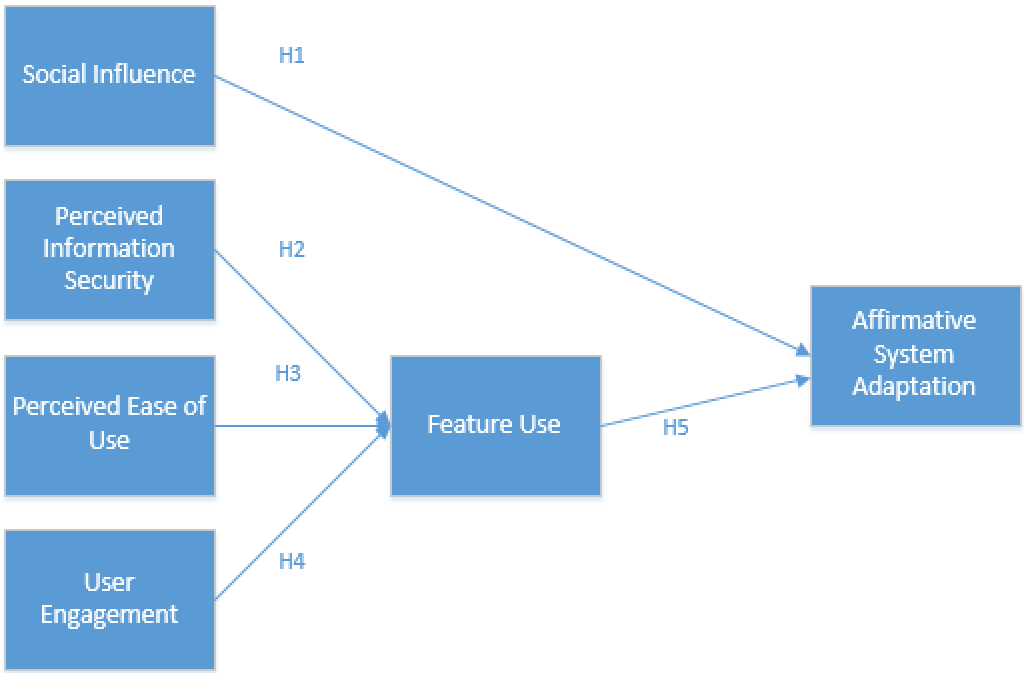

Figure 12 Conceptual Adaptation Model

3.1 Social Influence

If we step back to earlier notions of social influence defined in the psychology literature, we find a definition of *social influence* based on compliance, identification and internalization (Kelman, 1958). Compliance is defined to be when an individual appears to agree with others but withholds their dissenting opinion; identification is defined as when someone with authority influences an individual; and internalization is defined as an intrinsic acceptance of belief both in outward and internal conformity (Kelman, 1958). The social impact literature states that the strength, immediacy and number of people in a group guide social influence (Latané, 1981). If we merge the different concepts of *social influence*, the reciprocal effects of the individual's influence on an information system includes the strength and compliance of management to adapt to the changing needs of an information system. The definition of *social influence* thus shifts to comprise the communication between the user and manager, the perceived team input, group authority influence, and the access to the system of the user (Thomas and Bostrom, 2010). The *social influence* construct in the adaptation and continued use phase should answer the question: “Does the information system provide effective help in providing for user input, access to information, communication between team and leadership and adequate education on system functionality?” To answer this question we develop the following hypothesis:

> *H1: Individuals' social influence will positively impact affirmative system adaptation toward users' needs during the continued use phase.*

3.2 Perceived Information Security

Information security is defined as “the protecting of information and [minimizing] the risk of exposing information to unauthorized parties” (Venter and Eloff, 2003). Information security assessment occurs in the information systems literature regarding change management (Dawson, Watson and Boudreau, 2010), risk management (Sun, Srivastava and Mock, 2006; Zhao, Xue, and Whinston, 2013; Cavusoglu, Raghunathan and Yue, 2008), and business continuity management (Wang, Gupta and Rao, 2015), but it still requires assessment for use as a factor in adapting an information systems’ continued use. As an information system adapts to new regulations at both the federal and industry policy levels, the information system must maintain adequate continuity of function, security, and safety of information in order to protect the end user while maintaining feature use and organizational fit. However, technology changes regarding additional information security can amplify the duress of the information system user (D'Arcy, Herath and Shoss, 2014). Information security protocols are in place to protect sensitive information and restrict access to such information to a need to know basis; however, the protocols are also in place to induce individual user self-control and integrity (Hu, West and Smarandescu, 2015). The perceived information security construct should thus answer the question “Does the information system provide adequate security, continuity, safety and protection of users and users’ information?” This question leads to the hypothesis:

H2: Individuals' perceptions of information security will positively impact feature use during the adaptation and continued use phase of the information system.

3.3 Perceived Ease of Use

The Perceived Ease of Use construct in usability research exists in most acceptance models (e.g. Davis, 1989; Venkatesh and Davis, 2000; Venkatesh and Bala, 2008). Research has focused on investigating the effect that perceived ease of use has on the acceptance of an information system as opposed to the organizational context and the adaptation the system requires (Ke, Tan, Sia and Wei, 2012). Other studies have examined the ease of use construct regarding adaptation and assimilation within an information system and identified that frustration and low engagement among users debilitates the perceived ease of use of a system (de Guinea, Titah and Léger, 2014; Yen, Hu, Hsu, and Li, 2015). “Technostress” is a term used to describe the stress that users experience due to application multitasking, frequent system upgrades and the subsequent uncertainty. The consequent job-related effects of technostress on individual workload is a significant proponent of the ease of use construct due to the users’ need to cope with the new requirements and thus, signify the need for the information system to adapt (Tarafdar, Tu and Ragu-Nathan, 2010). When measuring feature use and the ability of the information system to adapt, it is important to consider the ease of use of the system. This leads to the next hypothesis:

H3: Individuals' perceptions of the ease of use of an information system will positively impact feature use during the adaptation and continued use phase of the information system.

3.4 User engagement

The underlying perception of representation in the adaptation and change of an information system and the motivating factors of the individual user's engagement are important elements to consider when making managerial decisions regarding how to improve an existing system. Shared governance is the mutual collaboration and responsibility of managers and end users to address issues that arise over the course of a relationship and trigger information system adaptations (Bstieler, Hemmert, and Barczak, 2015; Huber, Fischer, Dibbern, and Hirschheim, 2013). When organizations collaborate using an information system, including the employee and managerial relationship, they develop adaptive competency due to shared governance (Kohli and Tan, 2016). Drawing on shared governance streams of literature, found in the product innovation and management technology literature, both the employee and manager determine the focus of collaboration and carry mutual responsibility (Bstieler, Hemmert, and Barczak, 2015; Burnside and Witkin, 2008).

In the social media literature, cognitive representation, defined as an individual's perception of their representational significance, has an effect on an individual's inducement to use familiar features (Gati and Ben-Shakhar, 1990; Pan, Lu, Wang and Chau, 2017). However, in implemented information systems, cognitive representation and feature use analysis requires an understanding of their importance in practice. With cognitive representation, it is important to assess the individual’s engagement to determine the relative importance of the representation in the adaptation of the information system to match the individual’s actual use. In the e-learning literature, the sense of presence, or representation, that an individual feels is a keen indicator of an individual’s engagement and motivation to learn new features (Franceschi, Lee, Zanakis and Hinds, 2009). To this, we develop the next hypothesis:

H4: Individuals' perceptions of representation and motivation evidenced in user engagement positively impact feature use during the adaptation and continued use phase of the information system.

3.5 Feature Use

Users involved in recent information system implementations often exhibit lower levels of feature use and rarely suggest feature changes; however, management still anticipates that users will adapt to the new features (Jasperson, Carter and Zmud, 2005). From a managerial standpoint, information systems serve the organization’s needs, based on adaptable mechanisms, emphasizing the organizational fit and strategic alignment regarding modification of the features (Clarke, 1994; Niederman, Clarke, Applegate, King, Beck and Majchrzak, 2017). After advancing to the continued use phase, high use features within the information system continue to be foundational while withstanding changes made to the information system, and they remain so even with the addition of new features. Exploration or utilization of new features depends on the collaboration technologies available for the user and their adaptability to their workflow (Maruping and Magni, 2012). The gaining of sufficient experience, during the continued use phase of an information system, leads to an expectation that an individual user will utilize the system for more tasks than just the required activities (Yen, Hu, Hsu, and Li, 2015). The likelihood of a modification to an individual user's established habits decreases as the decision effort increases for use of new features (Hess, Fuller and Mathew, 2005). This leads to the final hypothesis:

H5: Individual feature use will positively impact affirmative system adaptation toward users' needs in the adaptation and continued use phase.

4.0 Methodology

4.1 Research Setting and Study Design

The setting for the research in this paper is a not-for-profit health care organization consisting of seven hospitals, primary care and specialty physicians, and other complimentary services. It serves one million community members in southwestern Virginia and it is the only level one trauma center in its region (Carilion Clinic, 2015). Higher-level contextual factors identified in previous research include location, organization, and environment attributes (Venkatesh, Thong and Xu, 2016). Our research setting identifies additional factors that constitute boundary conditions of the organizational context of the healthcare system in which the application of our model will display on the results.

The survey was developed using methods specifically adapted to the organizational context of a hospital setting (Moore and Benbasat, 1991). It was administered electronically to employees in the healthcare system, using their work email address, and it asked them how they interact with aspects of the EHR system, how they utilize support systems, and how they use new features found in the EHR. All members of the healthcare team that interact with the EHR received the survey and completion of the survey was voluntary and anonymous. The nursing informatics department collected the survey data over a one-month period and received 577 total surveys. The data collected did not include demographic information such as age, gender, and experience, and the various roles of the respondents within the hospital are presented in Table 7. Registered nurses (RNs) who provide direct patient care make up the majority of the respondents.

My Role is:	**%**
RN – direct care provider	86.64%
RN – Management role	9.05%
RTR	0.22%
LPN	2.80%
Patient Care Tech/Nurse Aide	0.86%
Blank	0.43%

Table 7 Respondent occupation distribution

4.2 Procedure

The survey first asked respondents to clarify their role and then to answer questions in four major categories: general, access to information, clinical documentation, and devices. Appendix A contains a complete list of survey items.   User-volunteered comments were solicited if respondents chose “Disagree” or “Strongly Disagree” to one of the questions in a given category. Additionally, respondents could provide comments in response to additional prompts at the end of the survey. We applied the adapted constructs, as identified in the hypothesis development section above, to derive meaning from the resulting data.

5.0 Analysis and Results

5.1 Validity Assessment

We used Partial Least Squares - Path Modeling (PLS-PM) to analyze the Likert scale data in the survey. We utilized reflective constructs for *social influence*, *perceived information security*, *perceived ease of use*, and *user engagement*, meaning that causality flows from the constructs to the item indicators. The indicators are thus manifestations of the construct and changing the indicators will not change the construct. The constructs of *feature use* and *affirmative system adaptation* are formative constructs, as they are formed by their indicator and by subsequent construct paths. The smartPLS software utilized for our analysis required the cleaning of the data and the removal of incomplete surveys. Of the 577 total surveys, only 509 surveys remained after cleansing. We then supplied our conceptual model to the PLS-PM algorithm, and produced the item weights given in Table 8.

Construct	**Survey item**	**Outer Weight**	**VIF**	**t statistic**	**p-value**
Social Influence	1	0.73	1.232	4.484	<0.001
	2	0.80	1.262	6.099	<0.001
	4	0.75	1.293	4.998	<0.001
Perceived Information Security	11	0.70	1.129	6.075	<0.001
	16	0.83	1.315	8.998	<0.001
	17	0.59	1.176	4.171	<0.001
Perceived Ease of Use	8	0.71	1.667	2.516	0.012
	9	0.70	1.668	3.183	0.001
	10	0.70	1.569	2.875	0.004
	14	0.79	1.361	4.63	<0.001
	19	0.70	1.277	3.817	<0.001
User engagement	5	0.70	1.099	2.38	0.017
	7	0.89	1.099	4.365	<0.001
Feature Use (R^2 = .11)	13	1.00	1.000	-------	-------
Affirmative system adaptation (R^2 = 0.07)	12	1.00	1.000	-------	-------

Table 8 Beta weights from path analysis

We can see from the outer weights that each exceeds 0.60 except item 17, which is just barely under the threshold at 0.59. All variance inflation factors are below three and all items have significance beyond 0.05. As such, our survey items should be deemed acceptable for use in construct evaluation.

To insure that the constructs we are testing are in fact what we measured, we analyzed the measurement scale. Based on Shah and Goldstein's (2006) method of evaluating structural equation modeling, we used latent variable correlation and average variance extracted (AVE) to test the discriminant validity. We examined the composite reliability, which should be greater than 0.70, and found that each construct exceeds this reliability threshold. Variance inflation factors (VIF) should not exceed three and none of of the constructs exceed that threshold. Average variance extracted (AVE) is on the diagonals of the correlation matrix. Each of the correlations should also be less than the square root of the AVE. For each construct the AVE should exceed 0.50, demonstrating that more of the construct attribution is attributed to the construct instead of random error (Shah and Goldstein, 2006). Each of these measures shows good convergent validity, divergent validity and reliability in our study (See Table 9).

Properties of Measurement Scales					Discriminant Validity					
	Mean	**SD**	**Comp. Rel.**	**VIF**	**1**	**2**	**3**	**4**	**5**	**6**
Feature Use	2.8	1.11	1	1.01	**1**					
Perceived Ease of Use	2.7	1.06	0.84	1.10	0.19	**0.72**				
Social Influence	2.7	1.11	0.80	1.01	0.13	0.53	**0.76**			
Representation Expectation	2.7	1.21	0.78	1.04	0.13	0.18	0.29	**0.80**		
Perceived Information Security	2.8	1.16	0.75	1.09	0.29	0.27	0.12	0.15	**0.71**	
Affirmative System Adaptation	3.2	1.13	1	1.00	-0.09	0.20	0.24	0.15	-0.07	**1**

n=509 √AVEs on diagonal

Table 9 Properties of Measurement Scales

We also tested the construct validity and fit of our model. Tanaka (1987) stated that the sample size to free parameters ratio should be at least 20:1 and Bentler & Chou (1987) stated that a ratio of at least 5:1 was acceptable. Our sample size of 509 with 15 free parameters exceeds the requirements suggested in both studies. Exceeding 200, our sample size is high for path modeling analysis indicating that the chi square statistic will always be significant and thus that it requires examination of at least one measure of absolute fit and one measure of incremental fit (Alwin and Hauser, 1975). The square root mean of residual (SRMR), which is an absolute measure of fit that measures the difference between the observed correlation and the predicted correlation, should be less than 0.08 (Hu and Bentler, 1999). The comparative fit index (CFI) and Tucker Lewis Index (TLI), displayed as incremental measures of fit should exceed 0.90, however, when the root mean square error of approximation (RMSEA) is below 0.158 then the CFI and TLI are less informative and should be examined with caution (Coffman and MacCallum, 2005; Edwards and Lambert, 2007). The RMSEA values of 0.01, 0.05, and 0.08 identify excellent, good, and mediocre fit and thus our model falls in the good to mediocre fit area (MacCallum, Browne and Sugawara, 1996). The Loglikelihood, AIC and BIC are comparative measures of fit and are only useful for comparison to other similar models and as a similar model to ours does not yet exist they cannot be applied. We used RStudio and the lavaan package to calculate our fit indices. See Table 10.

Model fit	
χ^2	224.302
d.f.	81
SRMR	0.054
CFI	0.904
TLI	0.875
Loglikelihood	-9793.82
AIC	19,665.64
BIC	19,830.7
RMSEA	0.059
RMSEA 90% C.I.	0.050 - 0.068

Table 10 Model Fit Characteristics

5.2 Qualitative Analysis Strategy

We used thematic analysis (Guest, MacQueen and Namey, 2012) to identify keywords derived from recurring themes discovered in the free response sections of respondents' surveys who selected “Disagree” or “Strongly disagree” to the main categories and to the free response prompts at the end of the survey that all respondents received. We followed the approach by Braun and Clarke (2006), where the thematic analysis occurs in six phases: familiarization with data, generating initial codes, searching for themes, reviewing themes, defining themes and producing final report. We utilized a pair of nurses that had expert domain knowledge of the themes associated in the comments sections, as they were already familiar with the data. Thematic analysis is a qualitative analysis method that is inherently interpretive research with potential bias based on who is analyzing the themes. To minimize this bias we use nurses from outside the study hospital. A separate section examines the text responses after summarization of the quantitative results.

5.3 Application of Conceptual Model

Appendix A displays the survey questions administered, in the order listed. We proceeded to test our hypotheses after alignment of the questions into the construct categories. We ran Bootstrapping with 5000 sub-samples, using a bias corrected and accelerated bootstrap to compute the path coefficients. See Table 11.

Hypothesized Path	Original Sample (O)	Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
H1 Social Influence -> Affirmative system adaptation	0.258	0.264	0.041	6.334	<0.001
H2 Perceived Information Security -> Feature Use	0.254	0.256	0.045	5.598	<0.001
H3 Perceived Ease of Use -> Feature Use	0.115	0.125	0.041	2.812	0.005
H4 User engagement -> Feature Use	0.077	0.084	0.041	1.869	0.062
H5 Feature Use -> Affirmative system adaptation	-0.124	-0.122	0.047	2.659	0.008

Table 11 Path modelling and Significance

Our first hypothesis examines the path between *Social Influence* and the *Affirmative system adaptation*, which is significant to <0.001. The set of survey questions identify how much perceived influence the individual has regarding the changes and adaptation of the EHR, and they examine the communication between the managers and employees to determine if they know who to contact if a problem arises and whether there is a problem resolution. This path had the highest coefficient in the model, showing that Social Influence has the highest overall influence on Affirmative system adaptation.

The path between *Perceived Information Security* and *Feature Use* of the EHR was the second hypothesis examined and it was validated with significance to <0.001. *Perceived Information security* has the second highest coefficient, demonstrating a high influence over *feature use* and adaptability in the EHR. Previous work has identified the relationship between individual feature use and outcomes such as a systems ability to adapt (Venkatesh, Thong and Xu, 2016). The set of questions comprising the Perceived Information Security construct determined the effects of security features, such as automatic sign out to avoid misuse by fellow employees, hand off reporting to transmit patient information to the next shift, and insuring adherence to medication rights. It is clear based on these results that information system security measures to keep patient data safe are very relevant to how features are utilized.

To our surprise, the Perceived Ease of Use of the model was the least influential factor on feature use and adaptability of the EHR, of those tested. Our third hypothesis examined the path between Perceived Ease of Use and Feature Use and was validated to a significance of 0.005. The Perceived Ease of Use path coefficient was about half the value of the more influential paths associated with Social Influence and Perceived Information Security. The questions for the Perceived Ease of Use construct determined if the display of information was easy to use, the ease of documentation, and whether there were appropriate amounts of information to support decision-making.

Unsupported at a p-value of 0.062, our fourth hypothesis examined the path between the User engagement and Feature Use. Though the User engagement construct was out of the 0.05 range of significance, the path coefficient is also the lowest in the model, showing it is also the least influential in assessing the *feature use* and *affirmative system adaptation*. The questions for the User engagement construct determined the perceived shared governance regarding collaboration in the changes to the information system, motivation for feature use and staying abreast of new information regarding the adaptation and changes to the information system.

Our fifth hypothesis examined the path between Feature Use and Affirmative system adaptation, which was significant to 0.008. The magnitude of the Feature Use Construct coefficient was the third highest of all the constructs but relative to the other predictor, Social Influence, was only half as impactful on Affirmative system adaptation. The Feature Use construct measured actual feature use in the information system and as a second level construct influenced by the three primary constructs: User engagement, Perceived Ease of Use and Perceived Information Security.

5.4 Text Response Analysis

Our survey included the ability for respondents to provide comments to specific areas in the main categories when selecting “Disagree” or “Strongly Disagree”. The survey asked all respondents to provide comments to the prompts of “The EHR would be better if” and “Provide additional comments”. Thematic analysis modeling analysis assessed each of the responses for distribution into categories. Many responses were specific to individual users, thus not generalizable, required exclusion.

In response to “I read the Clinical Informatics Update,” 34 respondents commented. The most common comment was that they were unaware of the Clinical Informatics Update (38.2%). Other responses included changes occurring too often (23.5%), not knowing where to go for help (23.5%), and not feeling they have input on changes (14.7%). Additional education on where to find the updates and involving users in updates to increase buy-in would assist in mitigating the concerns in these responses. The *user engagement* construct derives from users' motivations to stay engaged such as reading and being aware of changes and adaptations to the EHR. Mechanisms need to be in place for insuring staff’s awareness of updates and that proper representation of users in changes to the EHR will mitigate feelings of not having input on changes.

Themes identified in the comments provided for “I complete the majority of my documentation at the time I am with my patient,” returned 103 responses. One major theme identifies that clinicians are too busy charting at the time of patient care (90.5%), which indicates that they are documenting after providing patient care, which leads to gaps in the time between assessments and interventions and their documentation. This delay in documentation is a patient safety concern and addressable by improving the usability and decreasing the time in documenting assessments and care provided. The *affirmative system adaptation* construct derives from this question with the goal of understanding the EHRs ability to adapt to the users' workflow. It is clear that about 20% of all respondents feel that the design of the EHR has not yet adapted to their workflow.

When asked about use of the electronic worklist in the EHR, 94 respondents commented. The overwhelming theme of the comments (92.6%) indicate that staff do not use the worklist, some specifying that they cannot or do not need to. As the worklist is an optional feature, this question assessed whether users were using new features. The *feature use* construct derives from this question to ascertain use of new features, in this study a particular feature. As about 20% of the total respondents do not use this feature, management needs to take an initiative to promote the feature use or to educate staff on the benefits of using this feature if staff are to incorporate this feature into their workflow.

The responses to the question related to portability of the devices that respondents use provided 69 comments (see Table 12). The most common responses included connectivity issues (31.88%), devices being bulky (24.64%), and computers freezing (17.39%). Given that the most common "portable" device used in the hospital setting is a Workstation on Wheels (WOW), the response they are bulky is not surprising; however, these devices are sturdy and easier to clean and charge which makes them a good choice for this setting. Additional responses included computers being slow (10.14%), not having enough computers (10.14%), computers not being charged (7.25%), and the need for laptops (7.25%). Although these are not issues with EHR usability, the identifying and addressing of some of these problems could improve user perception of the EHR by improving efficiency of the documentation process.

Theme	%
Connectively issues	31.88%
Bulky	24.64%
Computers freeze	17.39%
Slow	10.14%
Not enough units	10.14%
Not charged	7.25%
Need laptops	7.25%

Table 12 Themes Identified in Device Portability

The question “What would make the EHR better?” solicited 271 comments. Analysis showed similar themes to previous commented sections thus it was considered that previous questions may have influenced the responses, but it is impossible to determine. See Table 7 for a summary of the themes identified. The most common responses were reducing redundant charting (17.34%), flowsheets being too dense (11.44%), and staff desire for input on changes (9.59%). Reappearance of redundant charting and flowsheet denseness responses show the importance of these feature flaws as areas of potential improvement, however respondents still indicated they would like user input on changes to the EHR. A stronger user input system would not only improve usability but also improve buy-in from users, as they would feel a connection to the EHR. Additional themes identified to this response include a desire to copy columns forward (5.54%), poor connectivity (3.32%), a desire for additional education regarding EHR use (2.58%), and a desire to chart by exception (2.58%). An usability error within the system exists as designed because columns should copy forward. Responses for continuing education increased over previous questions. 2.21% of respondents commented that they would like: less frequent updates, the ability to customize the EHR, notification of changes, and more computer terminals. Table 13 presents additional themes, showing a unique area to improve usability, safety, and clarity of the EHR.

Theme	**%**	**Theme**	**%**
Redundant charting was reduced	17.34%	More computers	2.21%
Flowsheets were not as dense on the screen	11.44%	Too many clicks	1.85%
Staff had input on changes	9.59%	Code documentation is difficult	1.85%
Copy forward	5.54%	Body they can chart on	1.85%
Connectivity is bad	3.32%	Search by text	1.85%
Education provided	2.58%	Ambulatory wants own settings	1.48%
Chart by exception	2.58%	Blood products	1.48%
Less frequent updates	2.21%	Dictate documentation	1.48%
Ability to customize	2.21%	Ability to remove lines	1.48%

Table 13 Themes Identified in EHR Improvement

Regarding the “provide additional comments” prompt, analysis of 207 comments revealed that 18.72% of respondents found that the flowsheets for charting are too dense and that there are too many places to chart information in one area. In addition, 15.27% of respondents found that the information they chart is redundant among the various areas, and that it would improve clarity to have only one place to document a specific assessment or intervention. Other comments given addressed the need for a separate place to chart information specific to different specialties (8.37%), not being aware of the required documentation list (7.88%), and columns not copying forward all of the information (6.4%). A small percentage (2.96%) of responses regarded the need for additional education in using the EHR, frequent updating of the EHR, the desire for the ability to free text, and the lack of practical use of charting by exception within the EHR. Table 14 provides additional categories. These comments suggest future changes to EHR flowsheet design, such as removing areas of redundancy and making modifications to improve the overall usability of the EHR, which could improve patient safety and save clinician time in charting.

Theme	%
Flowsheets too dense on screen	18.72%
Reduce redundant charting	15.27%
Separate vitals charting for each setting	8.37%
Did not know required documentation list existed	7.88%
Does not copy column when it should, copy forward	6.40%
Need education	2.96%
Too many updates	2.96%
Staff would like ability to free text in chart, no area to free text	2.96%
Charting by exception	2.96%
Codes are too difficult to document	2.46%
Tailor to patient	2.46%
Get input from users	1.97%
Ability to remove lines from chart	1.97%

Table 14 Themes Identified in Additional Comments

6.0 Discussion

Our motivation for this study was to advance the theoretical understanding of adaptation and use continuance of information systems while accounting for higher-level contextual factors in new conceptualizations of acceptance and use based on recommendations from the multi-level framework set forth by Venkatesh, Thong and Xu (2016). To explain the unique contextual factors present in healthcare systems we examine linkage of individual feature use to outcomes obtained while adapting the information system for better fit. Our major theoretical contribution with this study is the identification of factors that affect individual feature use and adoption of these features into the work routine regarding adaptation of the fit of the information system to perform its intended use. Our findings provide support for most of our hypotheses. First, the results show the likelihood of an individual feature's use having an effect on achieving expected outcomes of the information system and the ability to adapt toward that outcome. Second, the factors identified in the path analysis results determine the magnitude of influence on the system's overall adaptability.

The factors identified suggest that s*ocial influence* appears to be the most influential indicator regarding how users adapt to an information system in the continued use phase contrary to findings in usage and adoption (Johnson, Zheng and Padman, 2014). The degree to which an individual feels they have proper education and communication about adaptations and changes is the greatest indicator in our model regarding an information systems' ability to adapt and the likelihood of new features to be implemented into the existing workflow. Acquisition of assistance with adaptations to workflow had the second most impactful effect on adaptation of the information system. Another interesting finding is that users' ability to have direct input regarding changes was the least influential form of social influence. This may be due to attachment insecurity, shown to be a mediating factor in the leadership-employee relationship, regarding the suggestion of changes to a system and the preference of users toward guidance by authority figures, as long as there is proper communication and education by those authority figures regarding the changes (Rahimnia and Sharifirad, 2015). Individuals seem to be willing to comply with changes but the majority of individuals lack the intrinsic motivation to suggest changes on how to adapt the information system, based on our analysis of social influence and representational motivation. This agrees with the unsupported User engagement hypothesis and signifies that individuals desire leadership in change regardless of their perceived representation of the change and their lack of motivation to induce the change. However, the comment analysis showed that a small proportion indicated that they would like more input on changes made to the information system. Additional research should be conducted on what kind of personality in the user determines motivations to incite change. Managers could utilize these change motivated employees as staff advocates that could act a liaison between the less motivated employees and management.

Adaptation is necessary in the continued use of information systems. It is the responsibility of the manager to solicit the needed workflow changes to improve the information system. The most important action is then to communicate and educate the employees on how to use the new features as soon as the manager decides on changes. Education will be the leading factor in adopting new features and improving workflows.

7.0 Theoretical and Managerial Implications

The present study makes several contributions to theory. First, it extends prior research that has focused on usability and adaption in information systems based on the theory of reasoned action. Our study looks at the comprehensive magnitude of effect on feature use and outcomes in information system adaptation. We conceptualized how users' representation impacts adaptation in the information system and examined how the user influences individual features used and the overall task fit. We suggest that our adapted construct of *social influence* is the primary determination of exploration and exploitation of individual feature use. Hence, our work provides a foundation to further explore the concepts of adaptation and use continuance (e.g. teasing out the relative impact of leadership in promoting adaptation and implementation of new features).

Second, our study draws attention to examination of important higher-level contextual factors in regarding feature use and outcomes. Drawing on adaptations of the UTAUT2 framework, our study helps clarify the nomological paths that link usability constructs through the intermediate construct of individual feature use and the outcome of information system adaptation to improve task fit. In industries where workflow requires the use of multiple computer terminals, the information security protocols in place induce a fair amount of usability strain unless mechanisms are in place to ameliorate the encumbrance of constant logging in and out of terminals. We adapted the social influence construct utilized in the extant information systems literature and adapted the construct based on the psychology literature to accommodate the use continuance and adaption of an information system. We questioned the perceived value of representation necessary between the end user and manager when adapting an information system and found that, contrary to other organizational literature, end users would prefer to be led in change than incite change themselves.

To our knowledge, this is the first study to empirically demonstrate the relationship between usability, feature use and the outcome of task fit through adaptation. Prior literature has hinted about the importance of analyzing individual feature use and associated outcomes but a study of this topic has yet to come to fruition (Venkatesh, Thong and Xu, 2016). The present research validates this claim by formally conceptualizing and testing the role of feature use on outcomes of adaptation to task fit. Adaptation has been conceptualized in information system governance by complementary and substitution forms, however our study delves deeper into the understanding of adaptability through the relationship of the employee and manager (Huber, Fischer, Dibbern, and Hirschheim, 2013). Our results provide evidence of the importance of social influence as a leading factor in new feature use adoption. This has direct implications on the literature in information systems and healthcare and potentially for other streams where new features are implemented in an effort to improve technology fit. Furthermore, while prior studies have investigated adaptation and use continuance (Goh, Gao and Agarwal, 2016), our study contributes to the literature by the development and utilization of objective measures of use, adaptation, and fit.

Finally, our research extends the tradition of empirical research in the healthcare information systems domain by using a sample of 509 healthcare clinical staff and drawing on their experience with EHR features. Our design included data for a one-month period relevant to a time period when management was diligently trying to ascertain why features were not being used and attempting to examine the unnecessary strain placed on employees during use. Additionally, all clinical staff employees had the opportunity to respond to the survey. Overall, our design provides strong associative evidence about the impact of usability of individual feature use towards the value of the information system to the organization.

Our study contributes to practice by assisting decision makers in better understanding the impact of health information systems' ability to adapt to new features following a highly complex implementation. *Social influence* provides the best attribution for managers to examine leadership occurring in adapting information systems to improve workflow and employee satisfaction. The workflow of clinical staff in the hospital defines EHR use. Our study has identified that the most impactful areas for assessing and impacting usability and use include *social influence* and *perceived information security*. When changing the EHR and other aspects of technology use, interventions aimed toward improving the amount of communication and education for adapting technology use would be most impactful. From the text analysis, reducing the redundancy of charting, the amount of data on flowsheets, and streamlining documentation with fewer clicks and less scrolling would be valuable to improving the usability of the EHR. Additional changes that would improve workflow include having adequate physical supplies and conditions (computers and network connection), having the appropriate allocation of time to complete documentation, and having ample education and support to facilitate and encourage EHR use. Identification of organizational aspects impacting EHR use of individual users include creating lists and reminders aimed at making care easier and documentation aspects that prompt clinical staff to document care provided. The overall goal of improving patient safety and outcomes may also include devices to improve communication amongst members of the healthcare team.

7.1 Limitations and Future Research

Despite its many contributions, our study has some limitations. The conceptual model developed is generalizable to other types of information systems, however the survey items developed were specific to an organizational context of healthcare information systems. Future research may ameliorate this bias by adapting and reevaluating the survey items based on application of our conceptual model to new organizational contexts. To gain a deeper understanding of an organizational context it is best to collaborate with management and users of the particular organizational context to assist management in dually discovering use and adaptation issues for their context, while understanding theoretical applications that may interest the information systems academic community.

8.0 Conclusion

Despite the importance of investigations into adaptations of information systems, the lack of a sound conceptual framework that examines feature use inhibits research tradition in information systems. By integrating perspectives of new constructs, the proposed model provides a new direction for research on how information systems are adapting during their continued use phase. The implications of the model are currently applied to the healthcare setting but can be applied to new organizational contexts. The underlying foundation of the study is based on amalgamated information systems theories with the highest attributes from extensions of the UTAUT model. We hope that more effort will be utilized to extend the model to new domains and the effects assessed in the context of new and relevant constructs.

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Appendix A: Survey Questions

1. I have input into how we use Epic to document patient care.
2. If I have workflow questions, I have access to call someone to help me.
3. Submitting requests to change Epic is quick and easy.
4. The communication and education we receive for workflow changes or Epic content changes meet my needs.
5. My unit has EPIC SuperUser representatives.
6. Question uncollected
7. I read the Clinical Informatics Update (by email or posted on my unit).
8. Epic provides accurate information in a succinct format allowing access to the information I need when I need it.
9. The EMR provides a complete ‘picture’ of my patient.
10. I can easily tell what happened to my long term patient last week or during the days/nights I was off.
11. My unit uses Sign Out functionality in EPIC for continuity of care.
12. I complete the majority of my clinical documentation at the time I am with my patient or immediately following completing my assessment.
13. I use the electronic worklist in Epic.
14. I can easily see the activities and interventions required for the delivery of care for my assigned patients.
15. I currently complete routine narrative notes each shift in addition to my flowsheet documentation.
16. My Unit/Department uses the Epic handoff report to facilitate safe handoff of patient care (shift change, to OR, to Procedure).
17. I feel the electronic medication administration process (Bar Coding) facilitates the verification of the 5 Rights of medication administration.
18. I can easily and quickly document my assessments, rarely requiring me to work overtime in order to complete my documentation.
19. Required documentation is easy to complete using the Required Documentation list provided in Epic.
20. I am satisfied with the portability of the device I use to document.
21. The device I use today to complete my documentation allows me to document care at the patient bedside.
22. There are adequate devices available when and where I need it.

Chapter 4: The Reciprocity Effect in Online Healthcare Communities

1.0 Introduction

When an individual experiences a disturbance in their health state, he or she must first determine the type of care required and decide if they will seek help from a medical professional or handle the disturbance themselves (Chen, 2011). In response to the increased availability and accessibility of online health information in recent decades, patients have become more likely to opt for the latter. According to the Pew Research Center (2013), as of September 2012, 72% of respondents in the United States say they looked online for health related information. As healthcare systems face major challenges due to the scope and complexity of care needed by people with chronic illness, coupled with an increasing number of such patients, online health communities have been identified as a tool to facilitate high quality and affordable care for this demographic group (van der Eijk, Faber, Aarts, Kremer, Munneke and Bloem, 2013). Online health communities allow members with chronic illnesses to connect to a vast network providing both emotional and informational support to assist them in managing their condition (Yan and Tan, 2014). However, the actual effect of online health community participation on members' health is still debated. It is difficult to measure whether participation in an online health community results in an improvement in members' health states, and some concern exists regarding the quality of advice received through these social networks (Munson, Cavusoglu, Frisch and Fels, 2013). Although they can be challenging to study, online communities represent a rich source of patient data for research and analysis, because while traditional collection of patient data is often difficult due to privacy laws (Chen et al., 2012), members of online health communities freely share information.

Managing a chronic illness creates a burden on the individual diagnosed with it, the family members who support them directly and the healthcare system that provides their care (Vassilev et al., 2013). Multiple service appointments are required, and high demand for these services often leads to limited individual flexibility in making and changing these service appointments (Mirzaei et al., 2013). One chronic illness that impacts patients, families and service providers in this way is diabetes. Posing a major challenge to public health and individual patient health, diabetes is a major cause of heart disease, stroke and lower extremity amputations, each of which can be prevented with proper management and support (Stellefson, Dipnarine and Stopka, 2013). The Centers for Disease Control and Prevention (CDC) estimates that 30.3 million people in the U.S.—9.4% of the country's population—have diabetes (Centers for Disease Control and Prevention, 2017). Thus, patients with diabetes constitute a large demographic group with vast healthcare management needs, providing an excellent study population. Additionally, since most management of this chronic illness occurs in outpatient settings, leaving much of the responsibility for seeking treatment, adhering to physician advice and making lifestyle decisions in the patient's own hands, our research into online health communities has the potential to improve care management.

Researchers have observed that members of online health communities share disease management suggestions, provide social support to each other, and, through this support, gain confidence in managing their disease (Naslund, Aschbrenner, Marsch, and Bartels, 2016). Online health communities provide a method for cyber enabled patient empowerment, as members are motivated via online technology to take an active part in their healthcare management (Chen, 2011; Hsu and Lin, 2008). The mental anguish accompanying the diagnosis and ongoing management of a chronic illness motivates patients to reach out to members of the online health community in order to cope with their disease from an emotional perspective and to gain information about how to better care for themselves in light of their chronic illness (Haugbølle, Devantier and Frydenlund, 2002). Health communities also create social value, as they enable members to share information across geographically disparate locations (Goh, Gao and Agarwal, 2016). Some studies find that online health community membership improves patient-provider communication (Rupert et. al, 2014), while other existing research suggests that use of online health communities interferes with patient-provider communication (Bosslet, Torke, Hickman, Terry and Helft, 2011).

Given the varied findings about the efficacy of online health communities, it is clear that more research must be done, and soon. Over six million Americans search online for health information every day (Kanthawala, Vermeesch, Given, and Huh, 2016) and with so many people searching for health information online, the role and potential impact of online health communities has drastically increased (Nambisan, 2011). As more people seek to manage their chronic illnesses better in the outpatient setting, the support and information they receive through an online health community has an increased potential to impact their health and the costs of care (Gustafson et al., 1999). This is specifically applicable to diabetes: on WebMD, which is visited by more than 72 million people every month, diabetes is one of the top three most searched illnesses, with a 543% increase in searches related to complications of diabetes (Goodman, 2016). Diabetes management is complex and ongoing, needing daily attention, making continuous support, such as many patients find online, even more necessary (Wennick, Lundqvist and Hallström, 2009). Existing work suggests that online health communities are primarily beneficial because they provide patients with social support, meeting a need that the healthcare provider alone is typically unable to fulfill (DeHoff, Staten, Rodgers and Denne, 2016). Consequently, other researchers have examined how, through text mining algorithms potential safety concerns of treatments or medications can be discovered to aid in the informational support provided by online reviews and online health communities (Adams, Gruss and Abrahams, 2017; Goldberg and Abrahams, 2018). Unfortunately, without the knowledge that online health communities actually have a positive impact on members' health, it is difficult for providers to either recommend or discourage their use, creating another knowledge gap for patients.

Social support and patient adherence to medical treatments are associated with improving the reactions of online health community members to stress and, thus, causing an improvement in the health state (DiMatteo, 2004). Significant inquiry has been made to understand social value in online communities, spurring investigation of the modes of exchange between community members (Goh, Gao and Agarwal, 2016). Social support exchanges in online communities have been shown to benefit individual member's heath, providing one measure of social value (Yan and Tan, 2014). Another factor affecting of social value is reciprocity. For people managing chronic illness, social support has a greater impact (Embuldeniya, et. al, 2013) and thus reciprocity is an important consideration. Patients with chronic illness require long-term social support and researchers are investigating epidemiological and behavioral mechanisms to understand patient needs (Reblin, and Uchino, 2008). Although online community participation has been found to be associated with an improved health state for chronic patients (e.g. Berkman, Glass, Brissette, and Seeman, 2000; House, Landis, and Umberson, 1988; Rodriguez-Artalejo et al., 2006), it is not clear if the patients will return the favor to other community members and help build a reciprocal community good for providing long-term social support for its members.

In general, reciprocity is the process by which people reward kind actions and punish unkind actions (Falk and Fischbacher, 2006). Reciprocity has been measured in the face-to-face setting and more specifically to understand behavior and attitudes within organizational structures (Settoon, Bennett, and Liden, 1996). In the online setting, reciprocity has been found to promote good behaviors and cooperation among loosely related groups in disparate locations (Dellarocas, Fan and Wood, 2003). Specifically in online health communities, reciprocity has been studied in relation to its effects on social value creation in rural-urban disparities, the effects of reputation and knowledge sharing and the effects of patient empowerment (Goh, Gao and Agarwal, 2016; Zhang, Liu, Deng, and Chen, 2017; Johnston, Worrell, Di Gangi and Wasko, 2013; Fink, Yogev and Even, 2017). In online communities, reciprocal exchanges require cooperative capabilities in the transformation of assets, including knowledge contribution and social value (Xie, Wu, Xiao and Hu, 2016). Online communities are an example of general exchange using indirect reciprocity, as members can view other members' threads and thus benefit from the efforts of others. Online communities also contain direct reciprocity, where both members must contribute in order to benefit (Collins, 2010; Johnson, Faraj and Kudaravalli, 2014). Existing research has examined the general health impact of online health communities; however, we have yet to understand how the actual exchanges between community members affect individual members' health (Yan and Tan, 2016). In current research, it is also unclear if the receiving of social support in an online health community causes members to contribute to the community and thus build a social system of reciprocity which overall may impact the health of the online health community members (Yan and Tan, 2016). To address this research gap, our study investigates the role of reciprocity in potentially moderating the relationship between social support and changes in the health state of individual online health community members. In this way, we also examine the potential for online health communities to create social value and improve public health.

We pose the following questions. First, is reciprocity associated with the relationship between social support in the context of an online health community and a member's health state? Second, if reciprocity is associated with the relationship between social support received and a member's health state, does this reciprocity moderate the relationship? The ability of online health communities to provide support though social exchange allows for direct exchange of reciprocity and has a potential influence on health improvement. Through notions derived from social exchange theory and considerations of reciprocal control, we suggest that studying exchanges within the online health community will determine the value of reciprocity in improving members' health.

Examining reciprocity and social support, we test our assertion using a unique data set obtained from an online health community utilized by patients with diabetes. Diabetes, as previously discussed, provides an optimal study context since it is a chronic illness that requires daily, lifelong management and has a large patient population. The data set allows us to retrospectively observe all interactions in the community and the members' health states over a 73-month period. Our empirical results suggest that reciprocity does influence social support and impacts members' health states, demonstrating that higher levels of reciprocity promote a greater improvement in health.

Our study makes several contributions to the literature. To the best of our knowledge, this is the first study to empirically examine reciprocity as a moderator in the relationship between social support and health state improvement in online health community members. This theoretical proposition extends several streams of literature, combining social psychology and information systems models of reciprocity in social exchange. Additionally, prior research of online health communities has not provided an explanation for the improvement in members' health states or examined what causes modulations in the health state (Faraj, Kudaravalli, and Wasko, 2015). We make methodological contributions by analyzing four different methods for calculating reciprocity in an online health community and then determine the most rigorous way to measure reciprocity. Managerial implications of this study include unloading healthcare systems by decreasing the need for urgent, unplanned appointments, decreasing the incidence of negative side effects, and increasing the accessibility of free healthcare information and support.

The rest of the paper is organized as follows. First, we discuss the theoretical framework and develop our hypotheses. We then discuss our data and describe the variables. Next, we discuss our model and provide the estimation results. Finally, we discuss the implications of the results, conduct robustness checks and conclude.

2.0 Theoretical Framework

Members engaging in online health communities interact in a virtual environment in which a member can exchange social support with other members in order to gain the information they need to improve their health. To study exchanges in online settings, many scholars have used social exchange theory. Social exchange theory is based on the premise that exchange between individuals occurs with potential reward or cost, thus explaining social change as a process of this negotiated exchange (Homans, 1974). Mutual interdependence, used in early frameworks of social exchange theory, states that the social implications of interdependence in organizations and communities, such as reciprocal control, combines members' efforts in mutual and complementary arrangements in predicting outcomes (Cook, Cheshire, Rice and Nakagawa, 2013; Chadwick-Jones, 1976; Kelley and Thibaut, 1978). Our interest is the predicted outcome that occurs through these exchanges: an actual improvement in the member's health state. We understand reciprocity to be derived from the patterns of exchange that occur between two persons in the reinforcements of each other's actions (Ekeh, 1974). Social exchange theory provides three modes of exchange regarding reciprocity: a transactional pattern of interdependent exchanges, a folk belief and a moral norm (Cropanzano and Mitchell, 2005).

In this study, we examine four methods of measuring reciprocity and propose that the aggregate effects of the four methods of reciprocity measurement influence social exchanges between members in the online health community, leading to improved health. The four measures of reciprocity utilized in this paper include arc reciprocity, norm of reciprocity, mutual reciprocity and self-disclosure reciprocity. In the following sections, we first describe online health communities and social exchange, then develop our hypotheses, focusing on both the aggregate and individual reciprocal exchanges demonstrated in the interactions within the online health community.

2.1 Online Health Communities and Social Exchange

Similar to other virtual communities, in order for online health communities to be successful, foundations of trust must be established to facilitate social exchanges (Leimeister, Ebner and Krcmar, 2005; Alsharo, Gregg, and Ramirez, 2017). While social influence can be attributed to consensus effects, which include shared experiences and agreement regarding those experiences, the predominant motivation in online health communities may be the actual social exchanges that build knowledge contribution (Yan and Tan, 2017; Khodakarami and Chan, 2014). As previously mentioned, social exchange, defined as the giving and receiving of social support, has been shown to improve the health of members in online health communities (Yan and Tan, 2014). There is also an economic reward for maintaining social exchanges in an online health community, which is evidenced by the sharing of medical articles and experiences with diagnosis and treatments and provides the basis for meaningful exchange (Guo, Guo, Fang and Vogel, 2017).

3.0 Hypothesis Development

Our effort to understand how reciprocal behavior influences a member's health state is based on the social exchanges that occur between members of the online health community. Reciprocity in face-to-face interactions is a well-studied concept in social psychology literature and, in the context of online platforms, is also now studied by information systems researchers (Barak and Gluck-Ofri, 2007). Members use online health communities to obtain the necessary social support that they are unable to get from their healthcare providers or from a local support group, if one exists. Thus, as members balance the costs and rewards of using the online health community, they may feel a level of indebtedness toward the community. This feeling of indebtedness to others for their actions and the behaviors that flow from this sense of indebtedness constitute the norm of reciprocity. In the following section, we describe and hypothesize the fundamental role reciprocity plays in assisting members to obtain the rewards they seek.

3.1 Reciprocity

One recent stream of top-level research on reciprocity in online health communities focuses on reciprocity as a control variable, termed mutual reciprocity, and the likelihood that, in an exchange between two members, initiation by the first member will cause a reply by the second member (Goh, Gao and Agarwal, 2016). In other industries, reciprocity has been studied as it relates to power laws, leading collaboration and community size and resilience in online communities (Butler, Bateman, Gray and Diamant, 2014; Faraj, Kudaravalli, and Wasko, 2015; Johnson, Faraj and Kudaravalli, 2014). Other studies have examined participation and how reciprocity ties form in online communities, discovering how the most popular members of the online community receive preferential treatment from other members (Johnson, Faraj and Kudaravalli, 2014; Butler, Bateman, Gray and Diamant, 2014). Research on the influence of network structure identifies reciprocity as promoting an interactive give and take. Technology-mediated internalization, which stems from personality-based politeness behaviors, gender and ethnic stereotypes, is also impacted by reciprocity (Schmitz, Teng and Webb, 2016). Still other studies posit that the desire to enhance reputation explains contributions that occur without expectation of reciprocal benefit and provides acknowledgment of behaviors linking friendship, acquaintance or reciprocity (Faraj, Kudaravalli, and Wasko, 2015; Vaast, Davidson and Mattson, 2013). In organizational research drawing on social exchange theory, researchers have argued that norms of reciprocity accounting for individual exchange behaviors actually diminish the obligations of reciprocity (Beck, Pahlke and Seebach, 2014). Matook, Cummings and Bala (2015) assessed self-disclosure reciprocity on loneliness in online social networks and found that this particular measurement of reciprocity acts as a moderator. Drawing from existing research, we identify four ways of measuring reciprocity: arc reciprocity, norm of reciprocity, mutual reciprocity and self-disclosure reciprocity.

3.2 Social support received and arc reciprocity

Reciprocity can be measured in a variety of ways, and these methods have developed and shifted as reciprocity has come to be better understood. Katz and Powell (1955) first discussed constructing a measure of reciprocity after finding evidence that a tendency to reciprocate was a choice rather than a chance coincidence. Rao and Bandyopadhyay (1987) recognized that it is possible to measure reciprocity by looking at the number of symmetric ties or reciprocal pairs occurring in a social network. Utilizing this discovery, Lu, Guo, Lu and Chen (2015) created and tested a measure of arc reciprocity, finding it to be a more rigorous method of measuring reciprocity in social networks. Reciprocity, as a form of social capital, facilitates incremental knowledge integration in social networks, and using the arc reciprocity method captures knowledge integration by utilizing the incremental gains in reciprocal exchanges as a ratio of a member's entire social network activity (Lang, 2004). Knowledge sharing is an important aspect of membership in an online community, and as such, reciprocal knowledge exchanges are valued for their ability to sustain relationships necessary for community growth (Wasko and Faraj, 2005). Thus, we believe that arc reciprocity is a good way of measuring this aspect of interaction.

Thus far, arc reciprocity has only been tested in the corporate blogging environment to assess work related participation and job performance (Lu, Guo, Lu and Chen, 2015). We seek to determine if the rigor of this method is applicable in an online health community and determine its association with the relationship between social support received and members' health states. To make this discovery, we first need to compare the arc reciprocity method to other measures of reciprocity. Second, we need to determine whether, as an individual measure of reciprocity, arc reciprocity moderates the relationship between social support received and a member's health state. This leads us to our first set of hypotheses:

Hypothesis 1: Arc reciprocity positively influences the aggregate association of the overall reciprocity present in an online health community, thus improving a member's health state.

Hypothesis 2: Arc reciprocity positively interacts with the relationship between social support received and a member's health state.

3.3 Social support received and norm of reciprocity

The norm of reciprocity stems from the earliest forms of human interaction and states that we must repay in kind what is given to us (Whatley, Rhodes, Smith and Webster, 1999). Information, however, is given without the expectation of being repaid. A one directional exchange is possible with this system, but that potentially leads to the disruption of the structural balance. The idea of structural balance, first theorized by Heider (1958) and conceptualized as the balance between the give and take of social exchanges, is achieved through the norm of reciprocity. Additionally, in an online community, the member who receives support or information may not feel indebted to the member providing it, but rather to the community as a whole. The positive and negative exchanges that occur in a social network must balance or a state of cognitive dissonance will occur (Festinger, 1957). In an online community, cognitive dissonance occurs if a member 1) feels they are contributing more to the community than they are receiving, or 2) feels that they are taking more from the community than they contribute, with a sense of overwhelming indebtedness toward the community (Beck, Pahlke and Seebach, 2014).

In both cases, the member is out of balance and becomes detrimental to the online community.

In electronic networks of practice, which facilitate practice related information exchanges and are defined as emergent social networks, knowledge exchange facilitates a strong sense of reciprocity (Beck, Pahlke and Seebach, 2014, Wasko and Faraj, 2005). The norm of reciprocity was studied in a micro-blogging environment, but it has yet to be understood in the context of an online health community, and its association with the members’ health states have yet to be studied (Beck, Pahlke and Seebach, 2014). We seek to understand how the norm of reciprocity compares to other measures of reciprocity when assessing a member’s health state. Second, we examine whether the norm of reciprocity interacts with the relationship between social support received and the member’s health state. This leads to our second set of hypotheses:

Hypothesis 3: The norm of reciprocity positively influences the aggregate association of the overall reciprocity present in an online health community, thus improving a member’s health state.

Hypothesis 4: The norm of reciprocity will interact with the relationship between social support received and a member’s health state.

3.4 Social support received and mutual reciprocity

Mutual reciprocity differs from the norm of reciprocity in that it requires a mutual concession made by two parties, demonstrating a give and take expectation between two specific members of the community (Cook, Cheshire, Rice and Nakagawa, 2013). In a social network, this can be measured when there are social connections, referred to as edges, in both directions between two members (Goh, Gao and Agarwal, 2016). Mutual reciprocity is a derivative of generalized reciprocity behavior and is characterized by an ongoing, interlocking behavior where one member's behavior is contingent on another member's behavior (Baker and Bulkley, 2014). This is a direct form of reciprocity, with interactions occurring between two members who engage in continued exchanges that build knowledge as they maintain mutuality in their relationship (Johnson, Faraj and Kudaravalli, 2014). In an online health community, mutual reciprocity is the building of relationships between members, which may or may not impact the indebtedness they feel to the community as a whole.

Mutual reciprocity has been analyzed in relation to effects in urban-rural health disparities; in particular, researchers have examined whether a social network is formed randomly or if it evolves as an outcome of exchange patterns, and studies have analyzed its role in the creation of social value (Goh, Gao and Agarwal, 2016). At the organizational level, the effects of mutual reciprocity on member reputation have been tested (Baker and Bulkley, 2014). Also at the organizational level, research has found that the effects of social networks follow power law distributions. Power law distributions demonstrate that in the online community, some members have many connections while most members have very few connections (Johnson, Faraj and Kudaravalli, 2014). Mutual reciprocity has not been directly tested in terms of its impact in an online health community and, thus, its potential impact on members' health states. We seek to understand how mutual reciprocity compares to other measures of reciprocity when assessing a member's health state. Second, we examine whether mutual reciprocity interacts with the relationship between social support received and the member's health state. This leads to our third set of hypotheses:

Hypothesis 5: Mutual reciprocity positively influences the aggregate association of the overall reciprocity present in an online health community, thus improving a member's *health state.*

Hypothesis 6: Mutual reciprocity interacts with the relationship between social support received and a member's health state.

3.5 Social support received and self-disclosure reciprocity

Social exchange theory explains that individuals disclose information about themselves to aid in forming relationships. Thus, reciprocation is a benefit of self-disclosure, and inherent risk is the cost of self-disclosure (Posey, Lowry, Roberts and Ellis, 2010). Self-disclosure reciprocity is the most complex and robust concept of reciprocity, and it includes individual differences associated with personality traits, mood, gender, relationship type and group size (Ignatius and Kokkonen, 2007). Self-disclosure reciprocity is a unique phenomenon that has been studied with respect to loneliness and in concert with networking abilities and relationship orientation (Matook, Cummings and Bala, 2015). Since loneliness is common among chronically ill patients, self-disclosure reciprocity provides a process by which community members can become more receptive to social support (Chapman, Perry and Strine, 2005). One benefit of online communities is that their anonymity sometimes enables members to disclose information that they would not have the courage to disclose in a face-to-face interaction, thus providing the benefits of social support without a high cost of self-disclosure (Crisp and Turner, 2014). Relationship formation that occurs in early interactions of members in online communities has been shown to be improved through self-disclosure reciprocity; however, its impact on members' health states has yet to be studied (Wang, Burke and Kraut, 2016). We seek to understand how self-disclosure reciprocity compares to other measures of reciprocity when assessing a member's health state. Second, we will examine whether self-disclosure reciprocity interacts with the relationship between social support received and the member’s health state. This leads to our fourth set of hypotheses:

Hypothesis 7: Self-disclosure reciprocity positively influences the aggregate association of the overall reciprocity present in an online health community, thus improving a member’s health state.

Hypothesis 8: Self-disclosure reciprocity interacts with the relationship between social support received and a member’s health state.

4.0 Data and Variables

4.1 Research Context

In this paper, we conduct our research using a health social media website primarily oriented to patients with diabetes. The website, http://www.diabeticconnect.com/, allows for the interaction of members with similar health situations to promote the sharing of information about the medical devices they use, diet plans, laboratory values and medications, as well as offering emotional support from others who can relate to their experiences. Diabetes, in its various types, is found in 9.4% of the population in the United States and requires intensive daily management with regard to diet, exercise, medications (perhaps including injected insulin), and blood glucose monitoring—all of which is done at home (Centers for Disease Control and Prevention, 2017). People with diabetes may struggle with daily disease management that must be maintained for life; thus, they may feel overwhelmed and isolated and seek support from online health communities (American Psychological Association, 2013).

4.2 Dependent Variable

The dependent variable in our study is a member’s self-reported HbA1c value. The

HbA1c value is a measurement of the average amount of glucose in the blood over a three-month period and is generally collected during health checkups. The HbA1c value has been identified as a good indicator of the health state of a person with diabetes and is used by healthcare providers around the world as the standard method of assessing diabetes management (American Diabetes Association, 2017). Typically, patients have their HbA1c value tested every 90 days. In our study, we determine the rate of change in a member's health state by examining the first and last HbA1c values each member posted. A healthy HbA1c value for a patient with diabetes is below 6.8, although any decrease demonstrates an improvement in the health state (American Diabetes Association, 2017). HbA1c levels for a person that does not have diabetes range from 4.0-5.6. A person with diabetes can have an HbA1c value ranging from 4.0 (if their diabetes is very well controlled) to 18.0 or higher (if their diabetes is uncontrolled) (American Diabetes Association, 2017). Using these ranges, we also identify whether each member's last HbA1c value posted was healthy or unhealthy. See Table 15.

4.3 Focal Independent Variables

The focus of our study is the effect of the various measures of reciprocity on the relationship between social support received and a member's health state. We operationalize social support received as a reflective construct that combines the three forms of social support identified in Bambina (2007): informational support, emotional support and companionship. These forms of social support have been validated with methods described in Yan and Tan (2014). See Table 15.

Our moderator variables are the four different measurements of reciprocity identified in the extent literature: arc reciprocity, norm of reciprocity, mutual reciprocity, and self-disclosure reciprocity. Lu, Guo, Luo and Chen (2015) measured arc reciprocity utilizing a social network where each edge is considered separately and the reciprocity value is a ratio of the number of reciprocal paths to the total number of paths. Beck, Pahlke and Seebach (2014) measured the norm of reciprocity in electronic networks of practice as a dyadic interaction that occurs when a member responds to another member's post. Goh, Gao and Agarwal (2016) defined mutual reciprocity as "A measure of reciprocity in the network, which is estimated from a network statistic equal to the number of pairs of nodes i and j for which edges in both directions exist." Wang, Burke and Kraut (2016) measured self-disclosure reciprocity as a combination of five linguistic features including post length, emotional valence, the presence of certain topics, social distance between the poster and a person mentioned in the post, and how well the content of a post fits into social norms. We utilize the methods used in each of these studies to analyze the various measurements of reciprocity in our study. See Table 15.

4.4 Control Variables

To control for factors other than health state, social support received and reciprocal behavior, we include variables such as gender and tenure, defined as the length of membership in the online health community. Gender is posted on each member's profile page and is coded as "0" for female and "1" for male. It is important to note that diabetes is more common in females than males (Centers for Disease Control and Prevention, 2017). To obtain the tenure value, we subtract the number of days from the date the data was gathered to the date the member joined the online health community. See Table 15. See Table 16 for summary statistics. See Table A1 in the Appendix for the variable correlations.

Dependent Variable	Name	Measures	Reference
Patient's posted laboratory value	HbA1c	Patients' self-reported laboratory values	American Diabetes Association(2017)
Independent Variable	**Name**	**Measures**	**Reference**
Emotional support received	ER	Amount of emotional social support received in online posts	Bambina(2007)
Informational Support received	IR	Amount of informational social support received in online posts	Bambina(2007)
Companionship received	CR	Amount of companionship social support received in online posts	Bambina(2007)
Emotional support given	EG	Amount of emotional social support given in online posts	Bambina(2007)
Informational Support given	IG	Amount of informational social support given in online posts	Bambina(2007)
Companionship given	CG	Amount of companionship social support given in online posts	Bambina(2007)
Patient's membership duration	Tenure (days)	Time between date of joining the community and posting date	Yan and Tan(2017)
Gender	Gender	A dummy variable coded as 0 if female and 1 if male	Yan and Tan(2017)
Arc Reciprocity	Arc	Measures reciprocal behavior as a ratio to total social exchange	Lu, Guo, Luo and Chen (2015)
Norm of Reciprocity	Norm	A dyadic interaction that occurs when an actor responds to another's posting	Beck, Pahlke and Seebach (2014)
Mutual Reciprocity	Mutual	A measure of reciprocity in the network, which is estimated from a network statistic equal to the number of pairs of nodes i and j for which edges in both directions exist	Goh, Gao and Agarwal (2016)
Self-disclosure Reciprocity	SelfD	Combination of five linguistic features including post length, emotional valence, the presence of certain topics, social distance between the poster and a person mentioned in the post	Matook, Cummings and Bala, 2015; Wang, Burke and Kraut (2016)

Table 15: Variables and Measures

Variable	Mean	St. dev.	Min	Max
HbA1c	7.007042	1.620375	4.2	17.5
ER	10.47606	22.12067	0	206
IR	18.61127	38.404	0	391
CR	9.005634	22.60056	0	289
EG	6.752113	9.666502	0	58
IG	14.81127	20.53449	0	129
CG	14.02535	15.12957	0	76
Tenure(days)	1504.969	741.9869	24	3115
Gender	0.301408	0.459148	0	1
Arc	0.373273	0.245714	0	1
Norm	38.75775	69.87178	1	558
Mutual	12.07606	24.71416	0	260
SelfD	0.261456	0.200018	0	1

Table 16: Descriptive Statistics

5.0 Model

5.1 Conceptual Model

Figure 13 shows the conceptual model whereby we observe the relationship between social support received and a member's health state, examining how the measurements of reciprocity affect it aggregately and how each measurement interacts with the relationship. We have theorized that a relationship exists between social support received and a member's health state and that reciprocal actions made by members are associated with this relationship. We will explain these relationships in more depth in the mathematical form of the model in the next section.

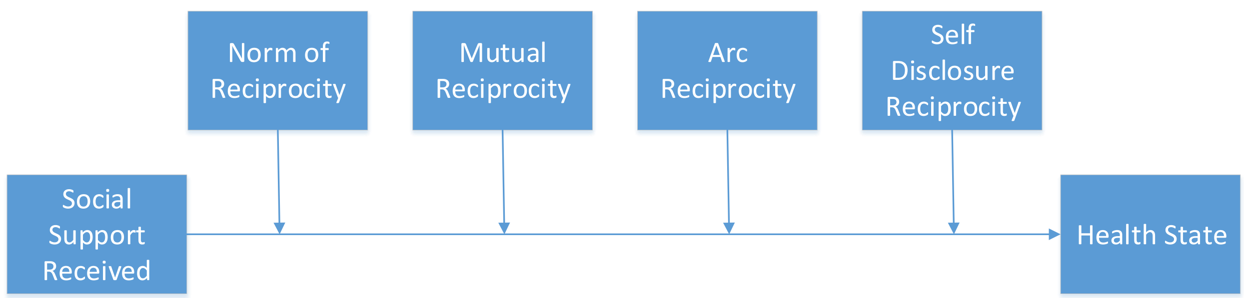

Figure 11: Conceptual Reciprocity Model

5.2 Mathematical Model

People belonging to an online health community receive social and informational support from others with similar health concerns to obtain relief for the stress and loneliness brought on by their diagnosis. Members of an online health community interact with each other in a variety of ways, including question and answer forums, sharing recipes and providing social support, each of which creates a social exchange that we utilize in our model. Members' self-reported laboratory values provide an objective dependent variable that allows us to quantify the member's health state. For members that post their laboratory values, we examine the different measures of reciprocity and social support in their posts and compare those measurements to the change in their laboratory values.

The degree to which members of the online health community demonstrate various types of reciprocal behaviors will differ from other online social contexts, like electronic networks of practice or corporate blogging. Our initial analyses, then, begin with an overall aggregate model to determine the combined effects of the four measures of reciprocity examined in information systems research: arc reciprocity, norm of reciprocity, mutual reciprocity, and self-disclosure reciprocity, on the members' health states. Utilizing methods similar to those used by Lu, Gupta, Ketter and van Heck (2016) and Yan and Tan (2017), we analyze our model. We examine the effects of the control variables, represented by vector D; reciprocity values, represented by vector $R_{i,t}$; social support received, represented by vector $S_{i,t}$; and social support given, represented by vector $G_{i,t}$, all on the HbA1c laboratory value for member i at time t. The $\zeta_{0,i}$ is the random intercept at the individual level, which allows us to incorporate heterogeneity to account for the varying effects not captured in our control variables. See Equation 12.

$$HbA1c_{i,t} = (\beta_0 + \zeta_{0,i}) + \beta_d D_t + \beta_r R_{i,t} + \beta_S S_{i,t} + \beta_G G_{i,t} + \varepsilon_{i,t}$$

Equation 12: Aggregate reciprocity model

In order to examine the effects of each measure of reciprocity to determine the interaction and moderation, we analyze individual models. We extend the first model by adding an interaction term in the form of $R_{i,t}$*$S_{i,t}$, where each measurement of reciprocity takes the place of R in the model. See Equations 13,14,15 and 16 for the mathematical models with the four measurements of reciprocity.

$$HbA1c_{i,t} = (\beta_0 + \zeta_{0,i}) + \beta_d D_t + \beta_r [Arc]_{i,t} + \beta_S S_{i,t} + \beta_G G_{i,t} + \beta_r [Arc]_{i,t} * \beta_S S_{i,t} + \varepsilon_{i,t}$$

Equation 13: Arc reciprocity interaction model

$$HbA1c_{i,t} = (\beta_0 + \zeta_{0,i}) + \beta_d D_t + \beta_r [Mutual]_{i,t} + \beta_S S_{i,t} + \beta_G G_{i,t} + \beta_r [Mutual]_{i,t} * \beta_S S_{i,t} + \varepsilon_{i,t}$$

Equation 14: Mutual reciprocity interaction model

$$HbA1c_{i,t} = (\beta_0 + \zeta_{0,i}) + \beta_d D_t + \beta_r [Norm]_{i,t} + \beta_S S_{i,t} + \beta_G G_{i,t} + \beta_r [Norm]_{i,t} * \beta_S S_{i,t} + \varepsilon_{i,t}$$

Equation 15: Norm of reciprocity interaction model

$$HbA1c_{i,t} = (\beta_0 + \zeta_{0,i}) + \beta_d D_t + \beta_r [SelfD]_{i,t} + \beta_S S_{i,t} + \beta_G G_{i,t} + \beta_r [SelfD]_{i,t} * \beta_S S_{i,t} + \varepsilon_{i,t}$$

Equation 16: Self disclosure reciprocity interaction model

We further recognize that the member's HbA1c value can be any feasible continuous value, providing an objective dependent variable that we can monitor for effects of reciprocity on the member's health state. Also, since this measurement is a continuous value, we do not need to conform the results to a logistically ordinal value set as other studies have done (Lu, Gupta, Ketter and van Heck, 2016; Yan and Tan, 2017).

6.0 Estimation Results

We deploy linear mixed-effects models using Eigen and S4, a form of semiparametric regression, to conduct the analysis for the multilevel data. We do this for two reasons: first, the reported laboratory values are diversely distributed, so general ordinary least squares models are inappropriate. Second, the data is exponentially distributed based on the number of posts, and thus smaller values for a variable are more common. The variations between health states based on laboratory values and reciprocal effects are inhomogeneous. For instance, more members with laboratory values that are close to healthy have more instances of reciprocity as opposed to members with laboratory values at either extreme end of the scale. To parse the individual effects of each measure of reciprocity we analyze five models. First, we examine the overall model and then we examine the individual moderating effects of each specific measurement of reciprocity. See Table 17.

		Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	Hypothesis	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
Intercept		Heterogeneous		Heterogeneous		Heterogeneous		Heterogeneous		Heterogeneous	
ER		0.339***	0.138	0.339**	0.151	0.359***	0.031	0.339**	0.145	0.339***	0.03
IR		0.304**	0.146	0.304**	0.154	0.304**	0.149	0.304**	0.145	0.304**	0.038
CR		0.399**	0.138	0.399**	0.167	0.399**	0.168	0.399**	0.169	0.399**	0.18
EG		0.359***	0.031	0.359***	0.032	0.359***	0.031	0.359***	0.031	0.305***	0.03
IG		0.409***	0.039	0.409***	0.04	0.409***	0.039	0.409***	0.039	0.409***	0.038
CG		0.305***	0.03	0.305***	0.03	0.305***	0.03	0.305***	0.03	0.305***	0.03
Tenure(days)		0.085*	0.045	0.080*	0.046	0.100**	0.047	0.094*	0.046	0.085*	0.046
Gender		0.147***	0.049	0.139***	0.05	0.147***	0.048	0.143***	0.048	0.146***	0.048
Arc	H1	0.293***	0.054	0.151**	0.06						
SSR x Arc	H2			0.107*	0.059						
Norm	H3	0.321***	0.055			0.081	0.103				
SSR x Norm	H4					0.046	0.039				
Mutual	H5	0.375***	0.04					0.220**	0.113		
SSR x Mutual	H6							0.016	0.033		
SelfD	H7	0.199***	0.064							-0.095	0.059
SSR x SelfD	H8									-0.083	0.057

Table 17: Results

We find a positive main effect of the combined measures of reciprocity on the members' posted HbA1c laboratory value (β[Arc]=0.293,$p<.01$; β[Norm]=0.321,$p<.01$; β[Mutual]=0.375,$p<.01$; β[SelfD]=0.199,$p<.01$). This confirms that reciprocity in general is associated with an improvement in the member's health state. Additionally, each measure of reciprocity is influential on a member's health state, and hypothesis 1, hypothesis 3, hypothesis 5 and hypothesis 7 are supported. When members are reciprocal in their social exchanges with other community members, they also show a greater health improvement. We check this result by dividing the sampled members into two groups, split by the median of the norm of reciprocity value, yielding a low reciprocity and a high reciprocity group that are nearly equal in size. We then use a two-sample t-test. We find that when compared with members demonstrating lower levels of reciprocity, those members with higher levels of reciprocity show a 0.41 improvement in health state, with a t statistic of 3.691***.

Our estimate results also support hypothesis 2. Consistent with the findings of a recent study in corporate blogging (Lu, Guo, Luo and Chen, 2015), we find that arc reciprocity moderates the relationship between social support received and a member's health state. More importantly, the method for measuring arc reciprocity was the only measure of reciprocity to have a significant interaction effect in the model. As Lu, Guo, Luo and Chen (2015) point out, arc reciprocity is the most rigorous measurement. In our study, too, it is the most rigorous method for calculating reciprocity, as it takes the member's full social network into account while examining the association between social support and health state. Specifically, arc reciprocity shows a suppression effect of about 29%, as it moderates the relationship between social support received and a member's health state. Thus, other models that are not examining reciprocal effects may be obtaining falsely elevated effects of social support due to suppression.

There is also an alternative explanation for the moderating effects of arc reciprocity: members with larger social networks do not necessarily interact with all of their "acquaintances." Friendly members may accept many invitations of friendship that do not lead to any actual social interaction in which to measure reciprocity. For instance, a high number of friends in the online health community equates to mediocre values of arc reciprocity, ranging from 0.30 to 0.50. It is unlikely that members with over 100 friends in the online health community will maintain reciprocity with each member, leading to this unique interaction effect of social support received and a member's health state.

The results of our analysis do not support hypothesis 4, hypothesis 6 or hypothesis 8. Although we hypothesized that norms of reciprocity, mutual reciprocity and self-disclosure reciprocity moderate the relationship between social support received and a member's health state, none of the interaction variables demonstrate an appropriate level of significance to support these hypotheses. However, without the moderating effect, each measure of reciprocity shows a significant association with changes in a member's health state. The fact that our results for the norms of reciprocity, mutual reciprocity and self-disclosure reciprocity do not show moderation may be due to members' lower levels of trust with the community and lower engagement in social interactions. It is possible, then, that trust and engagement play a pivotal part in the online health community, as they do in other types of online communities (Awad and Ragowsky, 2008; Leimeister, Huber, Bretschneider and Krcmar, 2009).

Our analysis demonstrates that social support given and received, as well as reciprocal interactions, can lead to an improvement in a member's health state. Although the interaction effects for most measures of reciprocity did not strengthen the relationship between social support received and a member's health state, reciprocity does play an important role in the social exchanges that occur in an online heath community. From a theoretical view, the fact that other studies have not examined reciprocity in the relationship between social support and health state indicates that they may have obtained falsely increased effects due to suppression. In our study, we find that when examining arc reciprocity, moderation occurs through the suppression of the relationship between social support and a member's health state. See Table 4 for a summary of results.

Hypothesis		Supported?
H1	*Hypothesis 1: Arc reciprocity positively influences the aggregate association of the overall reciprocity present in an online health community, thus improving a member's health state.*	Yes
H2	*Hypothesis 2: Arc reciprocity positively interacts with the relationship between social support received and a member's health state.*	Yes
H3	*Hypothesis 3: The norm of reciprocity positively influences the aggregate association of the overall reciprocity present in an online health community, thus improving a member's health state.*	Yes
H4	*Hypothesis 4: The norm of reciprocity will interact with the relationship between social support received and a member's health state.*	No
H5	*Hypothesis 5: Mutual reciprocity positively influences the aggregate association of the overall reciprocity present in an online health community, thus improving a member's health state.*	Yes
H6	*Hypothesis 6: Mutual reciprocity interacts with the relationship between social support received and a member's health state.*	No
H7	*Hypothesis 7: Self-disclosure reciprocity positively influences the aggregate association of the overall reciprocity present in an online health community, thus improving a member's health state.*	Yes
H8	*Hypothesis 8: Self-disclosure reciprocity interacts with the relationship between social support received and a member's health state.*	No

Table 18: Summary of Results

6.1 Robustness Checks

We further construct two variables to process online health community posts. The first alternative proxy captures the member's level of trust in the community and is constructed with the length of a member's profile text (Bellogín, Cantador and Castells, 2013) and whether the member posts a profile photo (Pempek, Yermolayeva and Calvert, 2009). Posting this information indicates trust, and the likelihood of self-disclosure increases due to increased responsiveness and disclosure-liking phenomena (Derlaga and Berg, 2013). The higher the level of trust with the community, the higher the level of self-disclosure a member is likely to have. In addition, we also examine other engagement variables, linking the number of friends and followers to the likelihood of mutual reciprocity. After including these variables in selected experiments in our model, our estimation results hold. Table A2 in the appendix provides summaries of these results.

7.0 Discussion

The prevalence of online health communities, as well as the amount of information and support available in these communities, continues to increase and grow. Of particular interest to researchers, and to healthcare management overall, are members and groups with chronic illnesses. As mentioned previously, patients with diabetes account for nearly ten percent of the population in the United States, constituting a very large demographic group whose health can be improved by better support, knowledge, and access to management strategies. Online health communities provide a means for people with chronic illness to obtain the social support that is not part of the typical patient-provider relationship. Social support has been shown to alleviate many of the psychological difficulties that occur with management of a chronic illness (Von Korff, Gruman, Schaefer, Curry and Wagner, 1997), and online health communities have the potential to provide that support with 24-hour access and regardless of geographic location. Reciprocity in social support relationships has been shown to be a good predictor of the level of satisfaction found in these relationships (Antonucci, Fuhrer and Jackson, 1990). As we discuss next, our findings echo these assertions.

We examine our findings by sub-setting the hypotheses into even and odd groups. The odd hypotheses were developed to explain how each of the four measures of reciprocity constitute an aggregate construct of generalized reciprocity. Our findings suggest there is significance in each of the measures individually, as well as aggregately. The even hypotheses were designed to explain the interaction that may exist between each individual measure of reciprocity and the relationship between social support received and a member's health state. Only one measure of reciprocity, arc reciprocity, shows a significant interaction, suggesting that arc reciprocity may be the only moderator in the relationship between social support received and a member's health state. Our findings also suggest that the arc reciprocity measurement is the most robust measure of reciprocity, which is in agreement with the findings of Lu, Guo, Lu and Chen (2015).

Our deeper understanding of reciprocity may be useful to the academic and healthcare communities at large, online health community designers and members of these online health communities. For the healthcare community, our findings support the argument that the use of online health communities is a viable option for improving overall patient health. Since the need for online health communities becomes more apparent in the breakdown of the patient-provider relationship, designers who are creating or redeveloping online health community platforms should take cues from our findings. Our study also provides encouragement for individual members of online health communities: they can be confident that their involvement and reciprocal interactions in such communities can improve both their own health and the health of other members.

7.1 Managerial Implications

Our work offers several managerial implications. First, the use of online social media as a source of social support, in the forms of emotional support, informational support and companionship, has increased. However, the value of these social interactions and exchanges is not fully understood, especially with respect to reciprocity. As the demand for healthcare increases, provider demand also increases and provider availability and accessibility decrease. Through providing support and information, online health communities can potentially relieve some of the scheduling pressure on healthcare systems. Acting on our findings that online health community membership and reciprocal behaviors do have health benefits and that increased reciprocity is associated with an improvement in health, medical professionals can more confidently promote participation in and perhaps even contribute to such communities.

For online health community designers and managers, our research identifies reciprocity as a key component of online health communities. When designing a new online health community or reimagining an existing one, the concept of reciprocity should be a central consideration and increasing reciprocal actions should be a design goal. Forums should promote self-disclosure and remind members of the anonymity of the posts, thus encouraging members to be more receptive of the social support available. In addition, designers should create methods to increase members' social networks in order to allow for an increased opportunity for reciprocal action.

7.2 Theoretical Implications

Individual behavior in online health communities is complex, as it is motivated by a nuanced set of contributing factors and dimensions. Although many of these dimensions have been identified and their effects in online health communities have been explored (e.g., Yan and Tan, 2014; Yan, Peng and Tan, 2015, Yan and Tan, 2017; Goh, Gao and Agarwal,2016), an understanding of exactly how reciprocity impacts these findings has been lacking, and the concept of reciprocity in social exchanges is thoroughly under-researched. Our study makes an important contribution to information systems research by qualifying what should exist in a reciprocity construct that can be examined across information systems, including social networking websites, work/practice online communities and online health communities. Our theoretical model incorporates both directional assessments of social support, four measurements of reciprocity and an objective dependent health variable. In our model, we highlight the importance of reciprocity in online social exchanges and examine the overall effect these exchanges have on a member's health state. More specifically, we propose the following arguments:

1. Anonymity in an online setting promotes self-disclosure, increasing member receptivity to social support.
2. Members that develop more social exchange connections and engage in reciprocal exchanges with a large social network experience a positive impact on their health state.
3. In research settings, reciprocity can suppress some of the analytic effects of received social support on a member's health state.

We advance theory through the inclusion of the reciprocity construct to determine the effects of social exchanges in online health communities and the overall impact this has on patient health. Originally, social exchange theory only posited the reciprocity principle as the reinforcing actions of two members in an exchange with each other (Kelley and Thibaut, 1978); however, through identifying several potential measures of reciprocity, we deepen the theoretical understanding of the reciprocity principle. At an abstract level, reciprocity should be considered as an aggregate measurement with several dimensions. A multidimensional measurement of reciprocity, which we term social exchange reciprocity, combines elements from several streams of theory stemming from social psychology and information systems research. The robustness of the arc reciprocity measurement contributes to the social network and relationship-building aspects of social exchange reciprocity; however, there is still a need to include self-disclosure reciprocity in order to have a complete construct. This is because only self-disclosure reciprocity can account for the linguistic features that shape a relationship, such as the valence, or mood, and breadth of communication in the reciprocal action.

In social exchange theory, Cropanzano and Mitchell (2005) identified reciprocity as patterns of exchanges, folk beliefs and moral norms; however, we extend this concept with the creation of social exchange reciprocity as an aggregate measure of reciprocity. By explicitly outlining the objective data points needed to understand reciprocal relationships, we have advanced the understanding of the effects of online behavior on social support and participant health.

7.3 Methodological Implications

We have chosen to test our model using text-mined data from an online health community. Such data allows for the minimization of subjectivity and bias associated with the Hawthorne effect. We also add to the argument for data mining versus survey methodical approaches, similar to other studies (Peña-Ayala, 2014; He, 2013), by extracting online health community data using text mining approaches. This is important because when using an objective dependent variable, such as a self-reported laboratory value, we need to ensure that study participants are being honest about their health states. From a methodological perspective, we identify reciprocity as a construct that is necessary to understand social support in the social exchanges taking place in online health communities. By comparing four different measures of reciprocity, we identify that arc reciprocity is the only measure robust enough to expose moderation effects in our context.

8.0 Limitations and Future Research

Some limitations exist in our study, suggesting pathways for future research. First, we only study one demographic group in one online health community. Future research should examine other demographic groups whose health can be objectively measured. For patients with diabetes, the HbA1c value provides an objective measurement, and other chronic illnesses may have similar laboratory values that can be tracked, allowing our research to be expanded and thus demonstrate generalizability. Second, we have assessed four different measurement methods of reciprocity and found that the arc reciprocity method was the most robust in the setting of online health communities. However, additional comparisons of the four reciprocity measures should be made in order to conclude that this is a replicable result. In addition, as we only studied members of the community that posted at least two laboratory values, there may be some inherent participation bias. As such, future work should address the effects of participation bias by creating an online health community that requires members to post their laboratory values but still allows for a holistic study of the population.

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Appendix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
HbA1c	1														
Gender_num	-0.16	1													
photo	-0.09	0.10	1												
profile_length	-0.06	-0.03	0.19	1											
membership	0.04	0.04	0.04	0.14	1										
IG	-0.26	0.07	0.29	0.18	0.16	1									
EG	-0.23	-0.02	0.30	0.20	0.21	0.76	1								
CG	-0.19	0.04	0.40	0.18	0.21	0.80	0.87	1							
IR	-0.09	-0.04	0.27	0.09	0.09	0.54	0.49	0.51	1						
ER	-0.10	-0.04	0.27	0.06	0.12	0.49	0.49	0.49	0.86	1					
CR	-0.12	0.03	0.26	0.09	0.16	0.55	0.55	0.56	0.87	0.90	1				
Norm	-0.19	0.03	0.28	0.13	0.21	0.79	0.69	0.70	0.81	0.79	0.81	1			
Mutual	-0.22	0.04	0.27	0.13	0.15	0.77	0.70	0.70	0.78	0.77	0.79	0.93	1		
Arc	-0.17	0.00	0.12	0.05	-0.10	0.31	0.33	0.32	0.34	0.32	0.32	0.35	0.60	1	
SelfD	-0.12	-0.02	0.11	0.05	-0.12	0.29	0.26	0.25	0.33	0.26	0.24	0.31	0.51	0.81	1

Table A1: Variable Correlations

Note: All variables are log-transformed. The average VIF is 3.70 and individual VIF is less than 10 (maximum is 6.559)

	Model 6 (Trust)		Model 7 (Engagement)		Model 8 (Trust and Engagement)	
Variable	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
Intercept	Heterogeneous		Heterogeneous		Heterogeneous	
ER	0.339***	0.131	0.339**	0.151	0.359***	0.031
IR	0.304**	0.15	0.304**	0.154	0.304**	0.149
CR	0.399**	0.16	0.399**	0.167	0.399**	0.168
EG	0.359***	0.031	0.359***	0.032	0.359***	0.031
IG	0.409***	0.04	0.409***	0.04	0.409***	0.039
CG	0.305***	0.03	0.305***	0.03	0.305***	0.03
Tenure(days)	0.085*	0.046	0.080*	0.046	0.100**	0.047
Gender	0.147***	0.049	0.139***	0.05	0.147***	0.048
Arc	0.293***	0.054	0.293***	0.054	0.293***	0.054
Norm	0.321***	0.055	0.321***	0.055	0.321***	0.055
Mutual	0.375***	0.04	0.375***	0.04	0.375***	0.04
SelfD	0.199***	0.064	0.199***	0.064	0.199***	0.064
Profile Length	0.765***	0.232			0.765***	0.232
Profile Picture	0.513**	0.257			0.513**	0.257
Num Friends			0.847***	0.212	0.847***	0.212
Followers			0.272	0.2	0.272	0.2
Following			0.012	0.27	0.012	0.27

Table A2: Robustness Estimation Results

Chapter 5: Conclusions

This dissertation creates the framework for a service system to assist in identifying interventions for improvement in the healthcare service ecosystem. Examination of the healthcare service ecosystem, through the lens provided in this dissertation, we discovered many specific service interventions made by professionals in taking responsibility of the service relationship and customers taking ownership of this relationship. By engaging the clinical staff, community and researchers, we demonstrate how the use of healthcare information systems improves the communication and performance of the healthcare system in the healthcare service ecosystem. Three service interventions were explored in this dissertation, leading to discoveries for assessing information systems, developing resilience metrics and identifying the effects of reciprocity.

In this dissertation, we develop new methods for examining the healthcare service ecosystem with the aim of gaining a better understanding of these processes. Through the creation of component resilience, a more granular method of examining resilience, and then applying this to the healthcare setting we have provided a new method for identification of the most impactful factors in a disaster. By examining the usability of the EHR, we identified that healthcare staff were reticent to initiate changes to the workflow independent of management and instead modified their own workflow in a less efficient manner. In examining the reciprocity of online health communities used by people with chronic illnesses, we have discovered the overall impact this has on the health state. Overall, we have utilized the healthcare service ecosystem as a basis for our research and have made both practical and theoretical contributions, also identifying many ways in which our research could be expanded.

There are many possibilities for future research directions within the healthcare service ecosystem. One possibility that could be explored is additional analysis of emergency department overcrowding, looking deeper at the inpatient hospital bed allocation. This would require data on how the inpatient beds are currently allocated and how the allocation is associated with the data gathered in the emergency department. We can then simulate different allocation patterns of inpatient beds and examine the effects it has on key performance indicators, such as length of stay. The goal of our analysis is to “rightsize” the hospital by allocating the appropriate number of beds for each kind of patient to optimize the system.

A second future research direction is to examine the effects of government policy on the healthcare services ecosystem. In particular, as we move from a fee-for-service to a fee-for-outcome paradigm of healthcare reimbursement, how can we monitor the performance of healthcare systems? Having an operational efficiency metric designed to compare the outcomes of similar sized healthcare systems would allow for assessment based on a fee-for outcome reimbursement scheme. Examining the effects of government policy on the healthcare services ecosystem provides another unique stream of research.

Finally, there are a number of provider and customer benefits derived from examination of the service relationship, mediation of the service relationship and interventions made by the parties. Adding additional patient demographic and diagnosis parameters to each of the models will enhance the possible roles these models play in healthcare system decision making. As this research progresses and more data is collected, deeper understandings of the effects of the patient or customer in the healthcare services ecosystem will be generalized.