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PATIENT–PROVIDER ENGAGEMENT AND ITS IMPACT ON HEALTH OUTCOMES: A LONGITUDINAL STUDY OF PATIENT PORTAL USE[1]

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Hospitalization of patients with chronic diseases poses a significant burden on the healthcare system. Frequent hospitalization can be partially attributed to the failure of healthcare providers to engage effectively with their patients. Recently, patient portals have become popular as information technology (IT) platforms that provide patients with online access to their medical records and help them engage effectively with healthcare providers. Despite the popularity of these portals, there is a paucity of research on the impact of patient–provider engagement on patients' health outcomes. Drawing on the theory of effective use, we examine the association between portal use and the incidence of subsequent patient hospitalizations, based on a unique, longitudinal dataset of patients' portal use, across a 12-year period at a large academic medical center in North Texas. Our results indicate that portal use is associated with improvements in patient health outcomes along multiple dimensions, including the frequency of hospital and emergency visits, readmission risk, and length of stay. This is one of the first studies to conduct a large-scale, longitudinal analysis of a health IT system and its effect on individual-level health outcomes. Our results highlight the need for technologies that can improve patient–provider engagement and improve overall health outcomes for chronic disease management.

Keywords: Patient portals, electronic health records, health outcomes, congestive heart failure, patient–provider engagement

[1]Viswanath Venkatesh was the accepting senior editor for this paper.

Introduction

Hospitalization of patients with chronic diseases poses an increasing burden on the healthcare system (Berwick and Hackbarth 2012). Hospital visits accounted for $387 billion in spending in 2015 and have become the focus of the United States government's Hospital Readmission Reduction Program (HRRP).[2] Patients with chronic diseases often need to consult with their healthcare providers and follow complex medical protocols (Ross et al. 2004). This makes management of chronic disease patients a difficult process, necessitating greater self-monitoring and care coordination among patients, caregivers, and their healthcare providers. Berwick and Hackbarth (2012) estimated that, in 2011, care coordination failure led to between $25 billion and $45 billion in wasteful spending.

A key issue in improving patient self-monitoring and care coordination is the implementation of health IT. Use of health IT systems has the potential to improve healthcare quality, reduce hospital visits and costs for patients, and consequently increase care efficiency (Bao and Bardhan 2017; Miller and Tucker 2011). However, recent evidence suggests that health IT designed to support provider decision making alone is insufficient to manage chronic diseases effectively (Kushniruk et al. 2009). For health IT systems to be effective, they need to provide patients with the opportunity to play active roles in managing their care and engaging with care providers (Osborn et al. 2010).

These prevalent needs for greater patient engagement have led to the emergence of a new class of software applications, namely, patient engagement systems. In recent years, adoption of patient engagement systems, such as patient portals, has accelerated, driven partially by incentives provided to physicians as part of the Health Information Technology for Economic and Clinical Health (HITECH) Act, enacted in 2009. The Centers for Medicare and Medicaid Services (CMS) provides incentive payments for healthcare providers to adopt and use patient engagement applications. However, in order to receive incentive payments, providers need not only adopt, but also demonstrate "meaningful use" of their patient engagement applications. Meaningful use regulations reflect the government's attempt to encourage effective use of health IT, including but not limited to patient engagement systems (Blumenthal 2011). In other words, the intent is to move away from rewarding healthcare providers based simply on the adoption of health IT systems, instead basing rewards on demonstration of effective use to achieve specific health outcomes. Therefore, in our context, use itself is not important but must be *effective* in the sense that it must help users attain desired goals.

From a theoretical perspective, we seek to answer the broader research question: *What is the impact of patient–provider engagement that is enabled by effective use of health IT on patient health outcomes*? From an empirical perspective, based on our context of study, our research question can be framed as: *What is the impact of effective use of patient portals on health outcomes of congestive heart failure (CHF) patients*? We focus on patients diagnosed with CHF because it represents one of the first two chronic health conditions covered by the HRRP policy on readmissions and affects nearly 5 million Americans (with 550,000 new cases every year) and accounts for more than $30 billion in annual healthcare expenditures.[3] CHF is a chronic disease that can lead to adverse events, such as emergency room visits and hospitalization, if not controlled and managed properly. CHF patients require active monitoring, provider engagement, and care management to ensure compliance with treatment protocols.

Researchers have stressed the need to understand effective use (Agarwal 2011, p. 1; Agarwal et al. 2010), but there are only a few studies of effective use in the information systems (IS) literature.[4] Burton-Jones and Volkoff (2017) observed that one reason is the difficulty of operationalizing effective use. There are a few relevant papers that provide a general approach to developing theories to *link IT system use to performance*—Burton-Jones and Gallivan (2007), Burton-Jones and Straub (2006), Burton-Jones and Volkoff (2017), Robert and Sykes (2016), Sykes and Venkatesh (2017), and Zhang and Venkatesh (2017).[5] Consistent with this body of work, the objective of our work is to develop a context-specific theory to link use of patient engagement systems to patient health outcomes. We adopt the framework developed by Burton-Jones and Volkoff as it provides an approach for developing a context-specific theory (rather than a general theory) of effective use (rather than generic system use) and how effective use can be linked to outcomes. However, they also argued that their work was an initial attempt to develop a platform for research on effective use and called for more research. "[By] demonstrating our approach in just one context, we are unable to claim broad generalizability of either the approach or theory. More research is needed before such claims could be made" (Burton-Jones and Volkoff 2017, p. 483).

[2]More information on this program can be found at https://www.cms.gov/medicare/medicare-fee-for-service-payment/acuteinpatientpps/readmissions-reduction-program.html.

[3]For more details, see https://www.cdc.gov/dhdsp/data_statistics/fact_sheets/fs_heart_failure.htm.

[4]For a detailed review, we refer readers to Burton-Jones and Volkoff (2017).

[5]Burton-Jones and Grange (2012) also provide a detailed account of effective use, but they did not provide a general framework to develop a context-specific theory (Burton-Jones and Volkoff 2017).

Burton-Jones and Volkoff's framework suggests that future research can theorize effective use by understanding salient affordances that can help achieve desired organizational goals and describe how these affordances can be actualized. They demonstrated their approach in the context of electronic health record (EHR) use and developed affordances primarily from the perspectives of use by healthcare providers. Examples of salient affordances they identified included data input, accessing data, clinical decision making, and managerial decision making. However, the healthcare system includes a *patient interaction and engagement* component that is not accounted for in their *effective use* framework. This is evident from the fact that patient engagement was included as part of the incentive requirements of the HITECH Act. Burton-Jones and Volkoff (p. 483) also consider this to be a significant limitation. "[The] picture we painted is still incomplete because we did not consider external stakeholders. A fuller picture could be obtained by considering external parties such as patients, agencies, and the government."

Our paper seeks to fill this gap by building on and complementing this extant body of research by extending the *theory of effective use to the context of patient–provider engagement*. The primary goal-oriented actors in our context are patients, although healthcare providers also play important roles as they are responsible for engaging with patients through the portals, as required (e.g., responding to patient inquiries). We identify salient affordances for patient–provider engagement that focus on patients' interactions with their healthcare providers. Hence, our theoretical contribution is to develop a *contextualized framework of effective use theory* in the context of patient engagement with providers—an important distinction from the prior literature that has focused primarily on provider use of health IT (Burton-Jones and Volkoff 2017).

Another theoretical and practical contribution of our paper is the development of a conceptualization and measure of effective use. When developing a conceptualization and measure of effective use, we need to be cognizant not only of the patient perspective, but also that of external stakeholders such as hospital executives and physician leaders at hospitals, policy makers involved in compliance with meaningful use initiatives, and clinicians involved in patient care delivery. To make decisions related to patient care, these individuals need *rich* conceptualizations and measures of effective use that can be collected with relative ease across individuals, locations, and time. Further, in order to make data-driven decisions, they need *conceptualizations and measures that are quantitative, objective, and allow causal inferences* with respect to the effectiveness of patient engagement systems. Frequent use of the specific subset of clinical features (***system***) by patients (***users***) to do specific ***task*s** constitutes *effective use* in our context. This conceptualization and measure of effective use captures all elements of use (user, system, and task) and is related to the final health outcomes. Although our conceptualization and measure is different from that of Burton-Jones and Volkoff, it captures the dimensions of their effective use conceptualization and measure (such as accuracy, consistency, and reflection in action) implicitly. Therefore, context-specific conceptualization of effective use theory leads to a rich conceptualization and measure of effective use, but at the same time, one that can be collected across a large set of patients and care delivery settings.

Our research also makes an important empirical contribution. To the best of our knowledge, this is one of the first studies to establish a causal link between patient- or user-level use and health outcomes at the individual level. Our study is also one of the first to focus on different types of clinical functions (or artifacts) that affect patient outcomes. There is a growing emphasis on the need for patient-level analysis using a longitudinal design to establish causal relationships between use and clinical outcomes (Angst et al. 2010; Gao et al. 2012), and our study fills this gap.

Our work has several practical implications. We quantify the impact of patient engagement with providers in a post-discharge setting. The meaningful use mandates of the HITECH Act emphasize patient engagement and coordination with providers as part of care management (Irizarry et al. 2015). Our work provides empirical validation that patient–provider engagement can lead to better health outcomes. Hence, our results provide a foundation to encourage policy makers to develop appropriate interventions that can spur portal use and greater engagement of patients with their care providers.

Background

Patient–Provider Engagement

A patient portal is a secure, web-based application that allows patients to access their medical records anytime and anywhere. The basic functions available to patients include the following: reviewing summary reports from providers; checking medication lists; requesting medication advice and prescription refills; scheduling appointments online; viewing lab tests and results; exchanging secure messages with providers; receiving personalized health reminders and notifications about test results and upcoming appointments; paying medical bills online; checking allergy lists and immunization history; and disseminating patient educational resources. Although portals offer a broad range of functions, some features specifically relate to the process of clinical care, such as viewing lab results, messaging and communication with pro-

viders, requesting medication refills, and viewing health reminders. In contrast, other features, such as updating patient demographics, verifying insurance coverage, and resolving billing inquiries, are not directly related to clinical care, but rather aim to accomplish administrative tasks. We define the former set of features as clinical-oriented and the latter as administrative-oriented features, and use these definitions subsequently in our theory development.

Unlike personal health records that are maintained by patients, portals are tethered to an EHR system and are owned and operated by providers (Tang et al. 2006). Patient portals synchronize patient health data with a provider's EHR system, offering patients convenient, up-to-date access to their health records. As a result, an integrated portal provides patients and providers with an accurate snapshot of patient health information. The decision to invest in these systems and determine what types of patient data are available to patients is typically made by healthcare providers, who must also ensure the integrity, currency, and security of the data released.

In recent years, adoption of patient portals has accelerated, driven partially by incentives provided to physicians, as part of the HITECH Act, to adopt and use EHR systems. Stage 2 of the meaningful use program requires that at least 5% of a healthcare provider's patients be engaged in their care, either through an online portal or an electronic personal health record. Stage 3 mandates that more than 35% of all patients seen by a provider (or discharged from a hospital) should receive a secure message using the EHR or portal's electronic messaging function, or in response to a secure message sent by the patient (or authorized representative). These requirements have led to their widespread adoption, as nearly 57% of hospitals and 40% of ambulatory practices now use some type of portal.[6] The U.S. health portal software market accounted for $1.2 billion in total sales in 2015 and is expected to grow to $2.75 billion by 2020.[7] Recent anecdotal news suggests that over 70% of chronic disease patients prefer using online portals despite their concerns about technological complexity, and the growth in portal use can be attributed to the relative ease of access to patient data and their ability to engage directly with providers (Bryant 2017).

Literature Review

Although studying the influence of the use of IT systems on performance, it is important to understand that use alone is not sufficient (Seddon 1997). The use must be effective as well, where effective use refers to *that type of use that helps users attain desired goals* (Burton-Jones and Grange 2012; Burton-Jones and Volkoff 2017). The IS literature has long called for a shift from use to effective use to accurately study system use, in terms of its intended outcomes and the actions and interactions that constitute such use (Marcolin et al. 2000). However, a recent review of the literature suggests a paucity of studies on effective use because of difficulties in theorizing and operationalizing effective use (Burton-Jones and Grange 2012, p. 634). Recent work by Burton-Jones and Volkoff calls for developing context-specific theories of effective use. Our work fills this gap by developing a contextualized theory of effective use in the context of patients' engagement with their healthcare providers—a departure from the prior literature that has focused primarily on provider use of health IT.

Prior studies have operationalized effective use with qualitative measures such as accuracy, consistency, and reflection-in-action (Burton-Jones and Volkoff 2017). Complementary to this literature, we develop a quantitative measure. Prior studies on health IT have primarily focused on developing a better understanding of the factors that are associated with portal use (Gerber et al. 2014; Jung et al. 2011). Recently, a few studies have examined the effect of patient portals on patient outcomes (Grant et al. 2008; Harris et al. 2009; Holbrook et al. 2009; Kollmann et al. 2007; Tenforde et al. 2012). Table A1 in the Appendix provides a summary snapshot of prior research on the effect of patient portals (or similar applications) to offer a sharper contrast between previous studies and ours. As reported in Panel A, most studies were conducted either in a lab setting, as randomized controlled trials (Grant et al. 2008; Holbrook et al. 2009), or as uncontrolled trials (Kollmann et al. 2007), as well as a few field studies (Harris et al. 2009; Tenforde et al. 2012). The sample size typically involved a small number of patients and relatively short observation periods (ranging from 3 to 12 months), which limits their generalizability. Further, the relationships between portal intervention and patient outcomes do not establish causality because of the cross-sectional (or short observation period) nature of most studies. None of these studies conducted longitudinal analysis on a large sample, using granular measures of portal system use by patients.

There is an extant body of research on the impact of IT on individual, organizational, and industry-level performance, as summarized in Panel B. Overall, we observe a shortage of longitudinal studies on the impact of functional use of IT on individual-level outcomes. Few studies have been done on the impact of IT on individual-level outcomes in a healthcare context (Bardhan et al. 2015; Kane and Alavi 2008). However, the primary variable of interest in most studies represents organizational/group use of IT systems. We argue that it is important to study individual-level use of IT because

[6] https://www.marketsandmarkets.com/PressReleases/patient-portal.asp.

[7] *Ibid*.

organizational benefits can only be realized when individuals adopt and use systems in a meaningful manner (Devaraj and Kohli 2003; Venkatesh et al. 2016).

A few studies have examined individual-level IT use and its influence on individual performance (Venkatesh et al. 2016; Venkatesh and Sykes 2013; Venkatesh et al. 2011), and are highlighted in the first two rows of Panel B. However, there are some key differences. First, these studies are primarily cross-sectional in nature, wherein, although data was collected in a longitudinal manner, their measure of IT use was aggregated across time. Second, in order to address unobserved effects and establish causality more convincingly, we need panel data where health outcomes and IT use are observed repeatedly (in multiple periods) for the same individual (see Venkatesh et al. 2016). In the context of this study, our objective is to explore IT (i.e., portal) use by *patients* and the impact of patient–provider engagement on their long-term health outcomes. Third, prior studies have treated IT systems as a single artifact and examined system use as a whole, without considering the impact of use of specific functional features on outcomes. Our research addresses these critical gaps in the extant literature based on a large panel data set of patient-level use of health IT across a long, multi-year observation period that allows us to establish the causal impact of patient–provider engagement on their health outcomes.

Theory Development

To understand the impact of patient portal use, we draw on the theory of effective use (Burton-Jones and Volkoff 2017) to propose a conceptual model that considers the functionalities of patient portals and how patients use them to engage with providers to manage their care. According to the theory of effective use, an IT artifact offers its goal-oriented user the potential for actions (i.e., affordances) (Strong et al. 2014). It conceptualizes *effective use* as the effective actualization of affordances to realize immediate outcomes (Burton-Jones and Volkoff 2017). The impact of these interrelated, immediate outcomes may manifest through the achievement of overall goal(s) or patient health outcomes in the context of our research setting.

The primary actors in our context of patient–provider engagement are CHF patients, and their goal in using the portal is to manage their progression of CHF, a major chronic disease that is the most common diagnosis among patients who are 65 years or older. Our discussions with physicians at a large, academic medical center indicate that one of their main goals in treating CHF patients is to manage disease progression to avoid frequent hospital visits. Because hospital admission of chronic disease patients is a growing problem in the United States (Kilgore et al. 2017), we use the number of inpatient visits as a key health outcome variable in developing our theoretical framework.

Effective Use

We now explain what constitutes effective use in our context. We follow Burton-Jones and Volkoff's theory framework and define effective use as "a type of use that helps users attain desired goals" (2017, p. 469). Effective use comprises various aspects of information system use by users. Burton-Jones and Volkoff focused on several properties of effective use, including the accuracy of derived information in reflecting reality, consistency of users' utilization of the EHR system, and users' engagement in reflection-in-action. The main actors in their research context were healthcare providers and their goal was to evaluate how healthcare providers used the EHR system to provide patient care.

In our research context, the primary actors are patients who engage with their healthcare providers through the portal system. When developing a conceptualization and measure of effective use, we need to be cognizant not only of the patient perspective, but also of external stakeholders such as hospital executives and physician leaders at hospitals, policy makers involved in compliance with meaningful use initiatives, and clinicians involved in patient care delivery. To make decisions related to patient care, these individuals need *rich* conceptualizations and measures of effective use that can be collected with relative ease across individuals, locations, and time. Further, these conceptualizations and measures should be *quantitative and objective*, in order for policy holders to help establish the causal influence of effective use on overall health outcomes.

Burton-Jones and Straub (2006) argued that a rich conceptualization and measure of use should capture all the elements of use—user, system, and/or task. Examples of rich conceptualizations and measures include deep structure use (Robert and Sykes 2016; Sykes and Venkatesh 2017), and accuracy, consistency, and reflection in action (Burton-Jones and Volkoff 2017). Binary conceptualizations and measures, such as use or non-use, are lean as they reflect use alone and not its nature, involving the three elements (Venkatesh et al. 2008). Further, the rich conceptualization and measure should relate theoretically to other constructs in its nomological network. In our context-specific study of patient–provider engagement, there are two major constructs: *effective use* and *patient-level health outcomes*. However, the final outcome (such as inpatient and ER visits) can be complex and difficult to map effective use directly to the final outcome. Therefore, as suggested by Burton-Jones and Volkoff, we first break the

final outcome into immediate (intermediate) outcomes (such as medication and visit adherence) that are required to achieve the final goal(s). We then identify the subset of features of the patient engagement application that map to these immediate outcomes.

Patient portal functionalities can typically be classified into two categories: clinical and administrative (Jones et al. 2015). Examples of clinical features include viewing lab results, messaging with providers, viewing health summary, appointment scheduling, and requesting medication refills. Although administrative portal features, such as updating insurance and resolving claims, reduce the administrative burden on patients and providers (Kieft et al. 2014), they do not have a direct impact on patient health outcomes (DeLone and McLean 2003). Hence, we do not consider the use of administrative features as effective use of the portal.

In contrast, use of clinical features can have a direct impact on patient health outcomes (Fonda et al. 2009; Leveille et al. 2009). For example, efficient communication with physicians through secure messaging can enable patients to better engage in their care management process. Patients can engage with providers on the progression of their disease, discuss treatments, monitor/discuss lab results, and seek medication advice. The ability to share pertinent medical information enables patients to participate actively in care management beyond the clinical setting (Irizarry et al. 2015). Further, archived messages in patient portals offer a rich history of information that can help providers to understand patients' health conditions and manage the onset of disease symptoms (Sun et al. 2012). In this manner, frequent use of clinical portal functionalities can enable patients to achieve desired health outcomes (Hibbard and Greene 2013).

Taken together, we argue that frequent use of the specific subset of clinical features (***system***) by the patients (***user***) to do specific ***task***s constitutes *effective use* in our context, as it helps patients to achieve long-term health outcomes (e.g., inpatient and ER visits) through attainment of immediate outcomes (e.g., medication and visit adherence). This conceptualization helps us to develop a measure of effective use that is not only rich in information content, but also easy to collect and benchmark in real-world clinical settings and hence useful for external stakeholders.

Although we do not borrow directly from the dimensions of effective use proposed by Burton-Jones and Volkoff (pp. 474-477), our conceptualization and measure captures these dimensions. For example, use of a portal's clinical functions, such as access to test results and medical history (health issues, immunizations, and allergies), can yield greater accuracy and consistency of information for both providers and patients. Similarly, portals enable patients to access and review their medical records and test results, reflect on them, and then decide how to engage with providers and whether or not to continue their treatment—an example of a *reflection-in-action* dimension of effective use.

Figure 1 represents our conceptual research framework that shows how affordances are actualized through effective portal use into immediate outcomes and overall patient health outcomes. Table 1 provides a detailed description of our conceptual framework and describes the major IT artifacts involved in portal use, affordance constructs, salient affordances that are actualized through effective use of the portal's clinical features, and their relationship to immediate patient outcomes and their overall health outcomes.

Affordances

We adopt Strong et al.'s (2014, p. 69) definition of an affordance: "the potential for behaviors associated with achieving an immediate concrete outcome and arising from the relation between an *artifact* and a *goal-oriented actor(s)*." The literature indicates four types of mechanisms that can enable improvements in health outcomes of users (Otte-Trojel et al. 2014). These mechanisms are (1) entering and accessing patient health information, (2) inter-personal continuity of care, (3) activation of information, and (4) service convenience. These mechanisms represent *affordances* because they provide the potential for patients to manage the progression of chronic disease, and arise from interactions between patients and IT artifacts (i.e., portal features).

Based on the theory of effective use, actualization of affordances through the use of portal functions (i.e., IT artifacts) can lead to desirable outcomes, by enabling patients to better manage their health conditions. However, the relationship between affordances (i.e., actions) and outcomes can be complex. Burton-Jones and Volkoff (p. 470) suggested that higher-level outcomes, such as managing chronic disease progression of CHF, can be achieved through "a linked set of more immediate concrete ones." Based on our discussions with several physicians at our research site, to understand what constitutes immediate outcomes for CHF patients, the ones that were identified as being critically important include (1) patient visit adherence, (2) adherence to medication regimen and treatment plans, and (3) patients' understanding of their overall health.

We further break down these three affordances into eight salient affordances, as shown in Table 1. Specifically, the three salient affordances related to the *entering and accessing patient data* affordance include verifying the completeness and accuracy of patient health information, viewing medication history and lab results, as well as viewing patient health

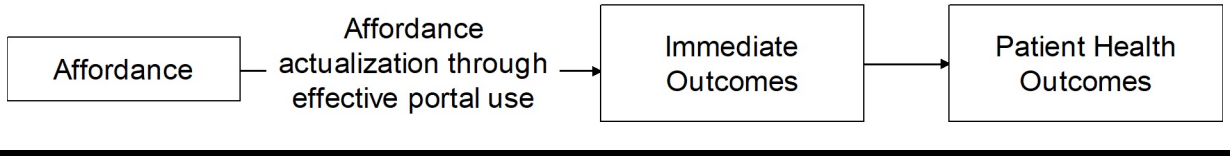

Figure 1. Conceptual Research Framework

Table 1. Affordances and Outcomes of Effective Portal Use by Patients

Responsible Goal-Oriented Actor	IT Clinical Artifact	Affordance	Salient Affordances	Immediate Concrete Outcomes	Patient Health Outcomes
Patients	• Lab results • Medical history (such as list of health issues, immunizations, and allergies) • Patient demographics and insurance coverage	• Entering and accessing patient data	• Verify completeness and accuracy of patient health information • Viewing medication history and lab results • View patient health summary	• Accurate and comprehensive information for both patients and providers • Improved understanding of overall health • Adherence to medical regimen and care plans	• Inpatient visits • 30-day readmission rate • ER visits • Average LOS
	• Secure messaging	• Interpersonal continuity of care	• Inquiries to providers about treatment plans • Respond to provider requests	• Improved care coordination and shared decision making • Monitor disease progression	
	• Prescription refill request • Appointment scheduling	• Service convenience	• Appointment scheduling • Request medication renewal	• Visit adherence • Adherence to medication regimen • Increase in patient satisfaction and self-efficacy	

summary. These affordances are enabled by the portal system that allows patients to interact with providers to ensure that patient health information is updated and verified in real time. The second affordance, *inter-personal continuity of care*, consists of two salient affordances—inquiries to providers about treatment protocols or medications, and responding to provider requests for health status. These salient affordances allow patients to engage personally with providers in discussing their treatment plans, resolving medication requests, and making dosage inquiries, thereby ensuring adequate monitoring of chronic disease progression. Finally, the *service inconvenience* affordance can be broken down into three salient affordances: requesting medication renewal, appointment scheduling, and providing consent to participate in telemedicine. These salient affordances provide patients with convenient options to engage with providers to refill prescription medications, schedule appointments, allow providers to make changes if necessary, and provide consent to the use of telemedicine by providers to engage in remote monitoring and online consultations instead of costlier, in-person office visits.

Next, we discuss how these salient affordances are actualized to achieve immediate concrete outcomes in the context of portal use by CHF patients. Finally, we discuss how these outcomes can help CHF patients realize their overall health goals.

Actualization of Affordances

Entering and accessing patient data: Patients with chronic diseases need access to their health records regularly to actively manage their health condition(s).[8] Patients can obtain an accurate and consistent view of their personal health status by accessing clinical portal features, because test results and medication information are typically available as structured data extracted from EHR systems (Burton-Jones and Volkoff 2017). Moreover, continuous review and tracking of health records can motivate patients and engage them to verify their personal health information for consistency and accuracy, thus ensuring the integrity of patient data (Otte-Trojel et al. 2014). Such patients are more likely to be aware of their treatment protocols, including medications and treatment plans, and can provide accurate and complete health information to their providers. Patients who are aware of their treatment protocols are more likely to adhere to their prescribed medical regimen (Paasche-Orlow and Wolf 2007). Therefore, we argue that frequent use of portals to access and update health information is associated with immediate concrete outcomes such as accurate and consistent information, improved understanding of overall patient health, and adherence to medical regimen. These immediate outcomes are translated into improvements in overall health outcomes, such as the number of inpatient and ER visits, as shown in Table 1.

Interpersonal continuity of care implies a continuous longitudinal relationship between patients and caregivers to promote self-management and care coordination between patients and providers (Parchman et al. 2002). Patient portals offer a secure messaging channel, compliant with the Health Insurance Portability and Accountability Act, which protects privacy and confidentiality of patient data. The use of secure messaging through the portal platform allows patients to communicate asynchronously with their preferred provider(s) at no additional cost and is relatively easy to use through mobile devices (Cole-Lewis and Kershaw 2010). Patients can describe their problems in detail without being time constrained, and care providers can research these issues carefully before responding (Sands and Halamka 2004, pp. 20-32). Further, portals allow patients to communicate with providers even when they transition from one care setting to another, which helps to maintain continuity in the patient-physician relationship (Saultz 2003). As patients use this channel more often, the richness of the two-way communication channel can lead to stronger social bonds and trust between providers and patients, and enhance the accuracy and consistency of patient health information available to providers (Saultz 2003).

[8]Health IT News. 2013. "Consumers Get Serious about Their EMRs" (http://www.healthcareitnews.com/news/consumers-get-serious-about-their-emrs).

The portal messaging feature also allows patients to review and mull over their clinicians' suggestions, clarify their treatment options, and reflect on their care plan and medication advice. As patients become adept at using portals, they play active roles in decisions related to their health; greater patient–provider engagement also allows patients to reflect on changes in their health data, that can lead to improved care coordination and shared decision making with providers and caregivers (Tang et al. 2006; Williams et al. 2005). The interpersonal dynamics of patient-physician relationships can also play a role in improving patient adherence and motivate patients to follow through on preventive treatment plans (O'Malley et al. 2002). Secure messaging allows caregivers to educate their patients on the importance of adherence to visit schedules and mitigate intentional non-adherence (Dayer et al. 2013) that, in turn, enables providers to accurately evaluate disease progression and make appropriate medication recommendations (Tebbi 1993). Therefore, effective use of portal messaging features actualizes an affordance that is similar to *reflection-in-action* because it allows patients to reflect on their treatments and facilitates immediate concrete outcomes, such as greater adherence to their medical regimen.

Service convenience: It is reported that 75% of patients with Internet access are willing to pay for online services, as service convenience is a major factor in their willingness to pay (Adler 2006; Roettl et al. 2016). Patient portals offer many features, such as online prescription refill requests, alerts, and appointment scheduling. Recently, patient portals have started allowing patients to provide their consent to engage with healthcare providers through telemedicine that also provides greater service convenience and avoids the need for in-person office (outpatient) visits. Therefore, portals provide a convenient experience that eliminates the hassles of conducting these transactions by phone or in-person visits. These types of portal-enabled interactions can lead to greater patient satisfaction with providers and the care delivery process (Otte-Trojel et al. 2014).

To summarize, we have proposed three affordances and eight salient affordances that can be actualized through effective use of patient portals, so that patients who engage frequently with their care providers through the portal functions (i.e., IT artifacts) are more likely to achieve immediate concrete outcomes. The interlinked immediate concrete outcomes can help patients achieve long-term patient health outcomes, such as reductions in inpatient and ER visits. For example, greater accuracy of patient information and improved care coordination can help doctors to analyze patients' health concerns carefully and provide accurate diagnoses (Venkatesh et al. 2011). Awareness about their health conditions further helps patients to understand the importance of preventive care and adherence to medical regimen (Paasche-Orlow and Wolf

2007) that in turn, allows providers avoid unnecessary changes to patient treatment plans (Avorn et al. 1998) that are commonly associated with unnecessary diagnoses, physician visits, and hospitalizations.

In sum, following Burton-Jones and Volkoff, we first define effective use in our context. Specifically, we argue that frequent use of the clinical features of a portal constitutes effective use in the context of patient–provider engagement. Building on the theory of effective use, we then identify salient affordances in the context of patient engagement. We then explain how actualization of these affordances through effective use of portals helps patients to achieve immediate concrete outcomes. Specifically, we describe how interlinked immediate concrete outcomes can help patients achieve long-term patient health outcomes, such as reductions in inpatient and ER visits. Hence, we posit that active patient–provider engagement, through effective use of patient portals, is associated with improvements in overall patient health outcomes.

> *Hypothesis*: *Effective use of patient portals is more likely to be associated with improvements in patient health outcomes, such as reduction in future inpatient and ER visits.*

Research Data

Our study setting consists of a unique and large dataset, drawn from patients who encountered at least one CHF-related hospital visit from 2002 to 2014, as recorded within the electronic medical record (EMR) system of a major academic medical center in North Texas. The patient portal was rolled out to patients of the cardiology clinic on January 1, 2004, although adoption and use of the portal happened gradually over time. Our observation period starts the first time that a patient encounters a CHF visit and ends after that patient's last visit to the hospital or clinic. This research design allows us to reduce patient and disease heterogeneity and focus on the impact of portal use on hospital admissions of CHF patients.

We tracked patient use of MyChart, one of the leading portal applications currently in use at a large number of major hospitals in the United States.[9] MyChart offers all functionalities described in the "Patient–Provider Engagement" subsection, allowing us to obtain a thorough evaluation of patient use of its various features, based on archival system logs. We measured patients' completion of different types of IT-enabled tasks (messaging, lab results viewing, medication refills, etc.) using the portal. We then matched patients' portal use to their admissions, across all hospitals in North Texas, using a regional enterprise master patient index identifier, provided by the Dallas Fort Worth Hospital Council Research Foundation (Bardhan et al. 2015). Hence, our panel dataset consists of matched records of portal use and their corresponding hospital (inpatient) and clinic (outpatient) visits, and includes 231,107 patient-quarter observations. We also matched patients' outpatient visits and portal use with their demographics, payer (insurance) type, and related comorbidities.

Dependent Variable

Number of CHF inpatient visits: We focus on objective measures of clinical outcomes, such as inpatient visits that are costly and serve as an important indicator of patient health outcomes. A CHF inpatient visit is defined as any hospital visit during which a patient is admitted to the hospital for more than 24 hours and is diagnosed with CHF as a primary or secondary diagnosis (ICD code of 428.XX). CHF patients need to engage periodically with their providers and failure to adhere to complex medical regimens can lead to frequent inpatient visits (Ross et al. 2004). We use the number of CHF inpatient visits as a key outcome, since CHF inpatient visits cost approximately $13,000 on average, while outpatient visits usually cost only a few hundred dollars (Bardhan et al. 2015). We also report results using other clinical outcomes, such as 30-day readmission risk, length of stay, and emergency department (ED) visits, in the robustness analyses section.

Independent Variable

Our independent variable of interest represents *effective use* of the portal, which we operationalize as the number of portal interactions related to its clinical features (i.e., IT artifact) such as messaging, medication refills/advice, and viewing lab results, in each quarter. Among our sample of 24,482 CHF patients, we observe that 21,216 patients never used the patient portal, while 3,266 patients used it at least once during this period to interact with their provider(s).

Control Variables

Patients' demographic characteristics can influence their portal use behavior, as well as the frequency of inpatient visits. We control for patient gender, age, race, and ethnicity because research has shown these variables to be influential

[9]MyChart is a tethered portal application from EPIC Corporation, a leading vendor of EMR software.

factors in patient-physician engagement (Cooper-Patrick et al. 1999). Because age can have a non-linear effect, we added a square term for age in our estimation models (Bardhan et al. 2015). *Male* (gender) is operationalized as a binary variable that takes a value of one, if a patient is male, and zero otherwise. *Race* is categorized into three binary variables: *African-American*, *Caucasian*, and *Other Race*. Because about half of the patients were Caucasian, we use *Caucasian* as the baseline variable in our estimation models. *Hispanic* (ethnicity) equals one if a patient is Hispanic, and zero otherwise.

We consider various payer types, including Medicare, Medicaid, self-pay, and commercial insurance. Because patients may switch payers during any observation period, we create several variables to capture payer information. *Medicare insurance*, *Medicaid insurance*, and *commercial insurance* are binary variables that are equal to one if a patient uses Medicare, Medicaid, or commercial insurance, respectively, during most of her visits in a given quarter. *Self-pay* represents the baseline payer type.

Patients' health conditions can influence their frequency of portal use as well as inpatient visits. Frequent comorbidities associated with CHF include diabetes mellitus, hypertension, peripheral vascular disease, chronic pulmonary disease, renal failure, anemia, alcohol abuse, drug abuse, and ischemic heart disease (Ross et al. 2008). Hence, we control for the total number of patient comorbidities, across all visits, during a quarter. Comorbidities are identified by the *Elixhauser Comorbidity Index*, based on the ICD-9-CM (International Classification of Diseases) diagnosis codes, because prior studies indicate the superior predictive performance of the Elixhauser index over Charlson index (Chu et al. 2010; Elixhauser et al. 1998).

Outpatient visits can serve as an indicator of patients' propensity to manage their health. Therefore, we control for the *number of CHF-related outpatient visits* and the total *number of non-CHF visits* in our econometric model. In other words, controlling for the number of CHF outpatient and non-CHF visits allows us to develop a sharper focus on the association between portal use and the frequency of inpatient visits, after accounting for other types of visits that patients incur during the course of their treatment.

Table 2 provides summary statistics of all model variables, as well as the distribution of use of major patient portal features. The major portal clinical feature that is exploited is the two-way messaging function that accounts for 49% of all clinical use, on average, in each quarter. Other than messaging, viewing lab results and medication refills are two intensively used functions. Overall, clinical features accounted for 76.87% of portal use, while administrative features accounted for the remaining 23.13%. Table 3 presents the correlation matrix that suggests that the pairwise correlations among our model variables are generally below the acceptable threshold for multicollinearity. We observe that the variance inflation factors of our variables are below the acceptable threshold of 10 (Greene 2003). We note that the average number of CHF inpatient visits per quarter for portal users is equal to 0.18, while the average number for non-users is 0.22. The difference is significant with a t-statistic that is equal to -14.94 (p-value < 0.01).

Empirical Analyses

In this section, we describe the specification of our main models and present the estimation results. Given that our dependent variable is right-skewed, we take a natural logarithm of all count data in order to mitigate skewness effects. We also present count data estimation results in the section on robustness checks.

Econometric Models

We describe two types of econometric estimation methods deployed in our analyses.

Two-Way Fixed Effects Model with Instrumental Variables

Although we control for several patient-specific characteristics, there may still be unobserved characteristics that are not accounted for by the control variables. To account for patient heterogeneity, we can either use a fixed or random effects specification. We use a Hausman test with the null hypothesis being that the unobserved individual effect is uncorrelated with the independent variables in order to choose a model specification. The Hausman test is statistically significant ($\chi^2 = 2676.58$, p-value < 0.01) that leads us to reject the null hypothesis and deploy fixed effects specification.

Heteroscedasticity is another concern due to incorrect standard errors. Following Wooldridge (2010), we conduct a Wald test with a null hypothesis of homoscedastic errors in a fixed effects regression model. The test rejects the null hypothesis of the absence of heteroscedasticity ($p < 0.01$); hence, we adopt robust standard errors to account for heteroscedasticity (Wooldridge 2010). Due to the possibility of a common time trend that affects inpatient visits and portal use,

Table 2. Summary Statistics

Variable	Total Number of Observations: 231,107			
	Mean	Standard Deviation	Min	Max
CHF Inpatient Visit	0.217	0.540	0	12
CHF Outpatient Visit	0.270	0.848	0	28
Non-CHF visit	0.637	1.750	0	45
Medicare Insurance (dummy)	0.378	0.485	0	1
Medicaid Insurance (dummy)	0.136	0.343	0	1
Commercial Insurance (dummy)	0.165	0.371	0	1
Elixhauser Comorbidity Index	2.110	1.391	0	9
Patient Age	58.88	17.039	0	104
Male (dummy)	0.498	0.500	0	1
African-American (dummy)	0.466	0.499	0	1
Other Race (dummy)	0.043	0.203	0	1
Hispanic (dummy)	0.182	0.386	0	1
Medication Refill Use	1.026	5.909	0	264
Appointment Scheduling Use	0.064	0.575	0	35
Two-way Messaging Use	4.792	26.413	0	1780
Lab Results Viewing Use	3.142	25.071	0	8062
Resolving Billing Inquiry	0.033	0.612	0	43
Use of Clinical Features	9.804	52.184	0	8163
Use of Administrative Features	2.950	17.019	0	972
Patient Portal Experience	0.945	3.468	0	43

Table 3. Correlation Matrix

	CHF Inpatient Visit 1	CHF Outpatient Visit 2	Non-CHF Visit 3	Medicare 4	Medicaid 5	Com. Ins. 6	Comorb. 7	Age 8	Portal Use 9
1	1								
2	**0.14**	1							
3	**0.05**	**0.12**	1						
4	**0.03**	-0.00	-0.00	1					
5	**0.02**	**0.01**	**0.03**	**-0.30**	1				
6	**-0.02**	**-0.02**	**-0.01**	**-0.34**	**-0.18**	1			
7	**0.23**	**0.21**	**0.03**	**0.03**	**0.01**	**-0.05**	1		
8	**0.02**	**-0.04**	**-0.13**	**0.48**	**-0.28**	**-0.13**	**0.10**	1	
9	**0.02**	**0.04**	**0.12**	**0.05**	**-0.07**	**0.15**	**0.03**	**0.03**	**1**

Note: CHF outpatient, non-CHF visit, Medicare, Medicaid, Commercial, Comorbidity, Age, and Patient Interaction are lagged variables. The correlation matrix with contemporaneous independent variables yields qualitatively similar results with respect to the significance of the pairwise correlations. Numbers in bold indicate significance at 0.05 level.

such as an update of providers' electronic systems, we include time fixed effects in addition to patient fixed effects, to account for these trends. Hence, our two-way fixed effects model is specified as:

$$\ln(in\_visit_{it}) = \alpha_0 + \alpha_1 \ln(P\_int_{it-1}) + \beta X_{it-1} + \gamma_i + \rho_t + \varepsilon_{it} \quad (1)$$

where i and t represent patient and quarter index respectively, in_visit_{it} is the number of CHF inpatient visits of patient i in quarter t, P_int_{it-1} represents the effective use of clinical portal features in the previous quarter, α_1 is the coefficient of interest, X represents a vector of time-varying exogenous control variables, γ_i is individual fixed effects, and ρ_t represents time fixed effects. The joint F test of time-fixed effects has a value of 8.77 (p-value < 0.01) that confirms the existence of a time trend. We also use lagged values of all covariates to partially alleviate the concern of reverse causality, as it is very likely that the impact of portal use in a given period (i.e., quarter) may not be observed in the same period.

The fixed effects specification does not account for time-varying, unobservable individual effects. If there are time-varying, unobserved effects that are correlated with both patient portal use and inpatient hospital visits, our estimation results will be biased. We address this issue by using an instrumental variable (IV) approach. For IV regressions, we need an instrument that is correlated with patient portal use but not directly correlated with inpatient visits. In our model, we use *portal experience*—measured by the number of years that a patient has used the portal—as an instrument.[10] We argue that patients who have used the portal for a longer period of time are more familiar with the system and, hence, are more likely to exhibit a higher intensity of portal use. In contrast, portal experience is unlikely to *directly* influence the frequency of inpatient visits in a particular quarter, and any impact is likely to be observed through patients' portal use. To ensure that our IV is relevant, we conducted a weak IV test using the Kleibergen-Paap (KP) Wald F-statistic that is preferred in the presence of heteroscedasticity. The KP Wald F-stat = 1613.44 and is larger than the critical value of 16.38 for the Stock–Yogo weak IV test (Stock and Yogo 2005) at 10% maximal IV bias size. Hence, we estimate a fixed effects model with an instrumental variable specification using two-stage least squares (2SLS).

[10]We thank an anonymous reviewer for this suggestion. We also tested an alternate instrumental variable, penetration of broadband access in the patient zip code. The alternate IV yields results that are qualitatively similar to the main results reported in the paper.

Difference-in-Differences Analyses

In our dataset, we observe patient behavior before and after use of the patient portal, and thus our research setting provides a quasi-natural experiment to study the relationships of interest. Hence, we implement a difference-in-differences (DID) estimation to control for the confounding effects of unobserved individual heterogeneity and macro shocks (Chan and Ghose 2013; Meyer 1995; Seamans and Zhu 2013).

We deploy a traditional DID (Ayabakan et al. 2017; Seamans and Zhu 2013) and the generalized DID (Chan and Ghose 2013; Dranove et al. 2003) specifications because they make slightly different assumptions. In a traditional DID specification, we separate patients into two groups with respect to their use of patient portals. The *Treatment* group consists of patients who have used the clinical portal features at least once, while the *Control* group includes patients who have never used the clinical portal features during the observation period.[11] This assignment enables us to create a binary variable *Treat* that takes a value of one for patients in the treatment group and zero for patients in the control group. To conduct a DID analysis, we compare the differences between changes in the frequency of inpatient visits of the two groups, before and after treatment. Hence, we construct a binary variable *Post* that equals one after treatment.

In a traditional DID model, we assume that the adoption time of a patient in the control group is the same as the adoption time of the most similar patient in the treatment group (Ayabakan et al. 2017). To find the most similar patient, we implement propensity score matching that allows us to reduce the endogeneity of group assignment (i.e., selection bias). We include both time-varying and time-invariant control variables, such as patient demographics, clinical visits, and payer type, as part of the matching strategy. The model specification for a traditional DID approach is

$$\ln(in\_visit_{it}) = \alpha_0 + \alpha_1 Treat_i + \alpha_2 Post_{it} + \alpha_3 Treat_i * Post_{it} + \beta Z_{it-1} + \varepsilon_{it} \quad (2)$$

where Z is a list of exogenous time-varying and time-invariant covariates to control for remaining patient level endogenous variation, and α_3 is the DID coefficient of primary interest. We do not include individual fixed effects because DID specification eliminates any time-invariant unobserved heterogeneity that is correlated with independent variables. We estimate a random effects model with clustered robust standard errors by patient (Chan and Ghose 2013) because the

[11]We also tested our models using an alternate definition in which the treatment group consists of patients who used the portal at least once for any type of function (instead of focusing only on clinical features).

Breusch and Pagan LM test (p-value < 0.01) indicates a significant panel effect. We also include time-fixed effects as a robustness check to ensure that our specification captures time trends.

As a complement to the traditional DID model, we also deploy a generalized DID model, following the approach described in Chan and Ghose (2013). We create a binary variable *P_adopt* to indicate a patient's portal use status in a given quarter. That is, *P_adopt* = 1 for the quarter in which the patient first uses the portal, as well as in subsequent quarters, and *P_adopt* = 0 before the quarter in which the portal was first used. We include individual fixed effects and time-fixed effects to account for any time-invariant individual heterogeneity and time trends that might raise concerns about endogeneity. Further, we control for time-varying heterogeneity by including several covariates, as specified in equation (1). To rule out concerns of reverse causality, we use the lagged value of *P_adopt* as the independent variable of interest following Dranove et al. (2003). Hence, the generalized DID model is specified as

$$\ln(in\_visit_{it}) = \alpha P\_adopt_{it-1} + \beta X_{it-1} + \gamma_i + \rho_t + \varepsilon_{it} \quad (3)$$

where coefficient α is the DID estimate of the effect of *P_adopt* on incidence of inpatient visits.

Estimation Results

We now report estimation results for the models described in the previous section. Model 1 in Table 4 represents the results of two-way fixed effects estimation with IV. As shown in Model 1, the coefficient of *portal use* is negative and significant (coeff. = -0.052, p-value < 0.01) that indicates that CHF patients who use clinical portal features frequently are more likely to exhibit a lower incidence of inpatient visits. To be precise, a 1% increase in portal use in each quarter reduces the number of future inpatient visits by 0.052%, holding other variables constant.

We also observe that the coefficients of *CHF-outpatient visit* and *non-CHF visit* are positive and significant that suggests that outpatient visits and non-CHF visits are associated with greater likelihood of inpatient visits. The coefficient of the *Elixhauser comorbidity index* is positive across all models and indicates that more comorbidities are correlated with a greater number of inpatient visits. The significant coefficients of *patient age* and its quadratic term clearly suggest a U-shaped relationship that confirms the age-dependent nature of CHF. Overall, the estimation results of Model 1 provide strong evidence to support our hypothesis with respect to the association between effective (clinical) use of portals and patient health outcomes.

Next, we turn to the results of DID analyses, following the approach described in the previous section. Table A2 in the Appendix presents the differences in ln(*in_visit*) between the *Control* and *Treatment* groups of patients along with test statistics, after propensity score matching. The first column reports the ln(*in_visit*) in the "pre-adoption" period, while the second column shows the ln(*in_visit*) in the "post-adoption" period. The third column presents the first difference between post- and pre-ln(*in_visit*), as well as the second difference of the change in the *Treatment* group versus change in the *Control* group. We observe that both groups show a significant decrease in ln(*in_visit*). Compared to non-users, patients who use portals effectively exhibit a 3.1% (p-value < 0.01) lower number of inpatient admissions, after controlling for other factors. Hence, our univariate DID analysis indicates that the reduction in inpatient visits among portal users is significantly lower than the corresponding reduction among portal non-users.

Models 2, 3, and 4 in Table 4 represent the results of various DID models with a rich set of covariates to account for confounding effects. Model 2 reports the results for traditional DID models and Model 3 reports the results for traditional DID with time-fixed effects. The interaction term, *Treat* * *Post*, is our focus of interest in both models. Model 2 indicates that patients who use portals incur 1.4% fewer inpatient visits compared to non-users. After controlling for time trends in Model 3, the variable *Treat* * *Post* becomes larger in magnitude, suggesting that portal users exhibit a 2% lower rate of hospitalizations compared to non-users. Model 4 presents the results of the generalized DID model. The coefficient of *P_adopt* is negative and indicates a 4% decrease in inpatient visits following portal adoption. Our results in Table 4 provide strong evidence that effective use of patient portals is associated with a significant reduction in inpatient hospital visits.

Robustness Checks

In this section, we describe several robustness checks that were conducted to address concerns that might potentially affect the empirical validity of our results.

Alternate Time Window

In the previous section, we used a quarter as our observation window. Because a three-month window may not be long enough to capture the effect of portal use on future inpatient visits, we also deployed a six-month window and re-ran the analyses using the models described earlier. Model 5 in Table 5 presents the results for a six-month time window. The

Table 4. Fixed Effects and DID Estimation Results

DV: ln(*in_visit*) = ln(CHF Inpatient Visit)	Model 1: Two-Way Fixed Effects with IV	Model 2: Standard DID	Model 3: Standard DID with Time-Fixed Effects	Model 4: General DID
Treat		-0.024** (0.005)	-0.020** (0.005)	
Post		0.023** (0.002)	0.008** (0.002)	
Treat * Post		-0.014* (0.006)	-0.020** (0.006)	
Portal Use	-0.052** (0.006)			-0.040** (0.006)
ln(CHF Outpatient Visit)	0.023** (0.003)	0.020** (0.003)	0.022** (0.003)	0.019** (0.003)
ln(Non-CHF Visit)	0.015** (0.002)	0.012** (0.002)	0.011** (0.002)	0.008** (0.002)
Medicare Insurance	0.001 (0.003)	0.008** (0.003)	0.009** (0.003)	0.002 (0.003)
Medicaid Insurance	0.006 (0.004)	0.015** (0.003)	0.014** (0.003)	0.006 (0.004)
Commercial Insurance	0.001 (0.005)	0.005 (0.004)	0.007* (0.003)	0.005 (0.005)
Elixhauser Comorbidity Index	0.021** (0.001)	0.028** (0.001)	0.028** (0.001)	0.020** (0.001)
Patient Age	-0.011** (0.001)	-0.002** (0.0003)	-0.001** (0.0003)	-0.010** (0.001)
Patient Age^2 (in 100s)	0.011** (0.001)	0.002** (0.0003)	0.002** (0.0003)	0.010** (0.001)
Male		0.020** (0.003)	0.018** (0.003)	
African-American		0.005 (0.003)	0.001 (0.003)	
Other Race		-0.017** (0.006)	-0.020** (0.006)	
Hispanic		0.019** (0.004)	0.014** (0.004)	
Constant	0.091 (0.059)	0.038** (0.008)	-0.071** (0.016)	0.126* (0.049)
Propensity Score Match	No	Yes	Yes	No
Individual FE	Yes	No	No	Yes
Time FE	Yes	No	Yes	Yes
R-squared	0.313	0.056	0.059	0.313
N	206,625	206,625	206,625	206,625

Note: Robust standard errors in parentheses. *p < 0.05; **p < 0.01.

Table 5. Robustness Analyses Results

	Two-Way Fixed Effects with IV estimation				
	Six-Month Time Window	Binary Portal Clinical Use	Alternate Outcome Variables		
Dependent Variable	Model 5: ln(CHF inpatient visits)	Model 6: ln(CHF inpatient visits)	Model 7: ln(CHF all-cause readmission)	Model 8: ln(CHF ALOS)	Model 9: ln(CHF ER visit)
ln(Portal Interaction)	-0.063** (0.011)	-0.226** (0.026)	-0.018** (0.003)	-0.114** (0.014)	-0.032** (0.004)
ln(CHF Outpatient Visit)	0.032** (0.004)	0.021** (0.003)	0.009** (0.002)	0.046** (0.006)	0.014** (0.003)
ln(Non-CHF Visit)	0.004 (0.003)	0.012** (0.002)	0.004** (0.001)	0.030** (0.005)	0.013** (0.002)
Medicare Insurance	-0.019** (0.006)	0.001 (0.003)	0.003 (0.002)	-0.001 (0.008)	-0.002 (0.003)
Medicaid Insurance	-0.004 (0.006)	0.006 (0.004)	0.007** (0.002)	0.011 (0.007)	0.005 (0.003)
Commercial Insurance	-0.012 (0.008)	0.003 (0.005)	0.002 (0.003)	0.003 (0.011)	-0.001 (0.004)
Elixhauser Comorbidity Index	0.014** (0.001)	0.021** (0.001)	0.009** (0.001)	0.045** (0.002)	0.017** (0.001)
Patient Age	-0.015** (0.003)	-0.011** (0.001)	-0.002** (0.001)	-0.024** (0.003)	-0.008** (0.001)
Patient Age² (in 100s)	0.015** (0.002)	0.011** (0.001)	0.003** (0.001)	0.027** (0.003)	0.009** (0.001)
Constant	0.205 (0.115)	0.085 (0.063)	-0.038 (0.028)	0.209 (0.133)	0.078 (0.041)
Individual FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.432	0.313	0.256	0.299	0.309
N	87,398	206,625	206,625	206,625	206,625

Note: Robust standard errors in parentheses. *p < 0.05; **p < 0.01.

results are qualitatively similar to our main models and indicate that portal use is associated with a reduction of 6.3% in the number of inpatient visits in the six-month window following portal use.

Alternate Measure of Portal Use

Next, instead of counting the number of times that patients used the clinical portal features, we deployed a binary variable to measure portal use. This variable takes a value of one if patient *i* uses the clinical portal features in quarter *t*, and zero otherwise. This specification allows us to focus on the aggregate effect of portal use, instead of the intensity of use. The results of this analysis are reported in Model 6 of Table 5 and are qualitatively similar to our earlier results. The coefficient of use is -0.226, indicating that, on average, portal users are likely to exhibit a 22.6% reduction in the number of inpatient visits compared to non-users, *ceteris paribus*.

We performed additional robustness analyses using 2SLS and alternate measures of portal use, as shown in Table A3 in the Appendix. Column M1 provides two-way FE (with IV) results for portal use, where users are patients who exhibit at least two quarters of portal interaction during the period of our study. In Column M2, use is defined as the number of times that a patient used only the two-way messaging feature of the portal application, and Column M3 includes portal use related only to messaging and medication refills. The results shown in Table A3 are similar to our main results with respect to the coefficient of portal interaction, and confirm that they are robust to small variations in the measurement of portal use.

Table A4 in the Appendix provides alternate estimation results of 2SLS with two-way fixed effects and DID models, where portal use is measured as the overall number of clinical and administrative interactions such as appointment scheduling and resolving billing inquiries. The results in Table A4 are consistent with our main analyses indicating that inclusion of administrative interactions in our measure of portal use does not significantly change our results.

Alternate Outcomes

Next, in order to test the robustness of our results with respect to the dependent variable, we expand our study to examine the effect of portal use on other outcomes of interest related to hospital visits, as shown in Table 5. For example, due to the increasing focus on hospital readmissions, we include *all-cause readmissions* as a dependent variable in Model 7, where a CHF patient may suffer a readmission due to any one of many diagnoses. Another metric is hospital *length of stay*, a common proxy for hospital efficiency. We derive the average length of stay (ALOS) by calculating the average number of hospital days stayed across all inpatient visits in a quarter for a given patient. Because CHF patients are vulnerable to ED visits, Model 9 presents the estimation results where the likelihood of an ED visit is measured as a binary variable. Our results indicate that actively engaged patients have fewer all-cause readmissions, shorter hospital stays, and fewer ED visits. These results are similar to the main results with respect to the positive association between intensity of portal use and patient outcomes. We observe that the impact of portal use on patient health outcomes is robust across model specifications and outcomes.

Count Models

We note that the dependent variable in our main models is a count variable that takes only non-negative, integer values, and has a skewed distribution. As an additional robustness check, we use count data models to estimate the impact of portal use on the count of inpatient visits. A Poisson regression is a common approach to estimate count data (Hausman et al. 1984). However, such a model makes strong assumptions of equal mean and variance. The standard deviation of the number of inpatient visits in our data is more than twice as large as its mean, suggesting the existence of overdispersion. The likelihood ratio test with a null hypothesis of zero dispersion rejects the Poisson model in favor of a negative binomial model with individual fixed effects. Hence, we first adopt a conditional fixed effects model proposed by Hausman et al. (1984), where the negative binomial regression is estimated using conditional maximum likelihood.

Next, we estimate a hybrid model that has a flavor of unconditional fixed effects (Allison 2005). The model in equation (4) is estimated using generalized estimating equations that allow for correlation among repeated outcomes for each individual and provides consistent parameter estimates even if the correlation structure is mis-specified.

$$in\_visit_{it} = \alpha_0 + \alpha_1 d\_P\_int_{it-1} + \alpha_2 m\_P\_int_i + \beta_1 d\_X_{it-1} + \beta_2 m\_X_i + \varepsilon_{it} \quad (4)$$

In the above equation, $d\_P\_int_{it}$ is the demeaned number of times that a patient portal is used by patient i at time t and $m\_P\_int_i$ is the mean of portal use for patient i. Similarly, d_X_{it} and m_X_i are vectors of demeaned and mean of time-varying control variables, respectively. The coefficient α_1 is the primary variable of interest.

We also report results using a count-data instrumental variables model developed by Mullahy (1997). This model is a generalized method of moments (GMM) approach for count data with endogenous variables and accounts for unobserved heterogeneity. We used the same instrumental variable as before (i.e., patient portal experience).

The results for the count data models are presented in Table 6. Model 10 represents the conditional fixed effects model. The coefficient of portal use is negative and significant, indicating that a one unit increase in the mean value of *P_int* is associated with approximately 4% (i.e., 100*(1-exp (-0.0004)) lower incidence of hospital admission. Model 11 reports the results of the hybrid model, and Model 12 illustrates the results of count data IV estimation. The results of the count data models are qualitatively similar to our main models and indicate that the intensity of portal use is significantly associated with a reduction in the number of inpatient visits.

Proportional Hazard Model

An interesting avenue for exploration is to examine the effect of patient portal use on the time duration between consecutive inpatient visits. Because inpatient visits are related to CHF diagnosis, the heterogeneity concerns at the visit level are mitigated. The typical method of handling repeated events during the observation period, as well as potential censoring, is to estimate a Cox proportional hazard regression for recurrent events. Following Therneau (1997), we used unordered failure events of the same type (Lee et al. 1992).

To address the challenge of constructing intervals for events such as hospitalization, we count the *number of days* between the last discharge date and next CHF inpatient visit as the

Table 6. Alternative Model Specification Results

	Count Data Models (Negative Binomial)			Model 13 (Recurrent Event Hazard Model)	
DV: CHF Inpatient Visit	Model 10: Conditional NB FE	Model 11: NB Hybrid	Model 12: NB IV Approach	Coefficient	Hazard Ratio
Portal Interaction	-0.0004* (0.0002)	-0.0004* (0.0002)	-0.002** (0.0004)	-0.001** (0.0001)	0.999
CHF Outpatient Visit	0.117** (0.017)	0.039** (0.006)	0.154** (0.009)	-0.163** (0.011)	0.850
Non-CHF Visit	0.068** (0.015)	-0.003 (0.006)	0.081** (0.013)	-0.133** (0.007)	0.876
Medicare Insurance	0.037 (0.030)	-0.074* (0.036)	0.213** (0.025)	0.125** (0.018)	1.133
Medicaid Insurance	0.087** (0.028)	-0.004 (0.036)	0.145** (0.024)	0.276** (0.020)	1.317
Commercial Insurance	0.018 (0.040)	0.0004 (0.054)	0.099** (0.031)	0.326** (0.024)	1.386
Elixhauser Comorbidity Index	0.196** (0.007)	0.096** (0.008)	0.339** (0.006)	0.332** (0.005)	1.393
Patient Age	-0.146** (0.011)	-0.112** (0.018)	-0.017** (0.002)	-0.028** (0.002)	0.973
Patient Age^2 (in 100s)	0.166** (0.011)	0.171** (0.014)	0.013** (0.002)	0.020** (0.001)	1.020
Male			0.068** (0.017)	0.032* (0.015)	1.033
African-American			-0.083** (0.029)	-0.127** (0.016)	0.881
Other Race			-0.050 (0.046)	-0.015 (0.039)	0.985
Hispanic			0.018 (0.032)	0.092** (0.020)	1.096
Constant	2.609** (0.294)	-3.057** (0.078)	-2.048** (0.068)		
Individual FE	Yes	Yes	No	No	
Time FE	Yes	Yes	No	No	
Mean Control	No	Yes	No	No	
Chi-squared	1533.57	—	—	7871.10	
N	125,628	125,628	125,628	56,132	

Note: Robust standard errors in parentheses. *p < 0.05; **p < 0.01.

length of each interval. We then count the number of times that the clinical features of the portal are used in each time interval as the independent variable of interest. The number of CHF outpatient visits and non-CHF visits are deployed as controls. We include additional patient-specific control variables, and robust standard errors are clustered by patient (Therneau and Grambsch 2000).

Model 13 in Table 6 presents the estimation results of the Cox proportional hazard model. The negative and significant coefficient of portal use demonstrates that patients with higher portal use have a lower hazard ratio of inpatient visits, thus exhibiting longer duration between hospital admissions. Specifically, each additional use of a patient portal reduces the hazard ratio by 0.001, meaning a 0.1% lower likelihood of incurring a hospital visit. The results of hazard model estimation are qualitatively similar to our earlier results.

Discussion

Our work draws on the theory of effective use, extended by Strong et al. (2014) and Burton-Jones and Volkoff (2017), to develop a context-specific theory framework focused on the impact of effective use of portals on patient health outcomes. Our research represents one of the first studies to explain how effective use of health IT systems can influence individual-level outcomes, in the context of patient–provider engagement. The results of our study support the efforts of CMS and healthcare providers to improve current levels of patient engagement as a way to enhance care coordination and delivery. These efforts will become increasingly important under the Affordable Care Act that places greater emphasis on reducing hospitalization costs by mandating bundled payments for a variety of chronic diagnoses, including CHF. Our results also support the focus on greater levels of patient engagement in stages 2 and 3 of the meaningful use program.[12]

Our results highlight the importance of patient–provider engagement by showing that active patient participation in decision making, care management, and self-care is associated with better health outcomes. They indicate that actively engaged patients are likely to have fewer emergency visits and incur lower hospital charges, even though they may exhibit a higher number of outpatient visits. Our results also imply strong financial incentives for patients to engage regularly with their providers after discharge and during care transition. In addition, payers and providers can also benefit from greater patient engagement. Our results are consistent with recent evidence from payers, such as Blue Cross and Blue Shield of North Carolina that implemented initiatives for patients to use online health services and encourage greater patient engagement (Caveney 2015).

Although we show that patient portal use significantly reduces the number of hospital visits for CHF patients and is associated with improvements across other health outcomes, we need to quantify the economic impact of portal use. In our sample, the standard deviation of portal clinical use is about 52 interactions per quarter. Among all patients in our data, the mean is nine interactions per quarter. If a patient increases her portal engagement by one standard deviation per quarter (i.e., 52 portal interactions), she will exhibit a reduction of 27.68% in hospital visits, based on the two-way FE model results. Considering that inpatient visits of CHF patients account for $65.2 billion in hospitalization costs in the United States (Voigt et al. 2014), our results suggest that converting all non-users to users (with the average number of interactions) would generate substantial savings due to lower hospitalization costs.

According to the Centers for Disease Control and Prevention, $315.4 billion was spent in the United States alone in 2015, to treat patients with CHF and stroke, with a large portion attributed to hospitalization.[13] Our calculations show that improving patient–provider engagement by increasing the intensity of portal use by one standard deviation from the sample mean is associated with a 9.58% reduction in readmission risk. Our results are consistent with anecdotal evidence. For example, Miami Children's Hospital deployed a self-service, mobile patient engagement application that was associated with significant improvements in overall patient satisfaction, utilization, and medication adherence, and increased patient engagement from 8% to 80% (Goldsmith 2016). We argue that healthcare providers who participate in value-based care delivery models can achieve significant cost savings and improvements in health outcomes by incentivizing patients to engage frequently through portals.

Our study does have a few limitations. It is restricted to patients diagnosed with CHF. Future studies can extend these models to study other chronic diseases such as diabetes, asthma, and chronic obstructive pulmonary disorder. We acknowledge that, although some constructs proposed by Burton-Jones and Volkoff cannot be directly mapped to our research framework, this is an opportunity for future research to further open the black box of the effective use of IT systems. Such studies can supplement Burton-Jones and Volkoff's grounded theory model-based approach with large-scale collection of portal use data by patients and care providers across time. Our model was based primarily on a study of inpatients and their portal interactions with providers within a single, large, academic medical center in an urban setting. Future studies may be designed to integrate data on portal use across different hospitals, health systems, and geographic regions to measure the impact of location, provider, and socio-economic characteristics on patient engagement. Although North Texas is fairly diverse in terms of its population, future studies are needed to expand the scope of our models to account for patient characteristics in other regions.

Conclusions

We examine the association between the use of patient portals and the incidence of inpatient visits for patients with conges-

[12]Health IT News. 2017. "Little-Noticed Stage 3 Meaningful Use Rule Could Pose Big Challenges for Hospitals" (http://www.healthcareitnews.com/news/little-noticed-stage-3-meaningful-use-rule-could-pose-big-challenges-hospitals).

[13]Chronic Diseases. 2016. "The Leading Causes of Death and Disability in the United States" (http://www.cdc.gov/chronicdisease/overview/).

tive heart failure. To the best of our knowledge, this represents one of the first efforts to extend the *theory of effective use to the context of patient–provider engagement* and conduct longitudinal analysis of *patient-level use* of health IT and its impact on various types of health outcomes associated with chronic disease management. Our results indicate that portal use is associated with a significant reduction in future hospital admissions of CHF patients. We also find that portal use has a beneficial impact on other patient outcomes such as readmissions, ER visits, and length of stay. Our research provides a roadmap to study other types of IS in general, and health IT in particular, using use interaction data that measure the intensity of individual-level system use and their impact on individual performance.

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Appendix

Table A1. Comparative Analyses of Related Literature

	Literature	Unit ofAanalysis		VA	Cont. and Binary Use	Theory	Outcome	Longitudinal (L) vs. cross-sectional analysis CS)	Methodology (models to evaluate effect of IT use on outcome)	Sample
		Outcome	IT Use							
Health IT	Tenforde et al. 2012; Harris et al. 2009	Patient	Patient	Yes	Yes	None	HbA1c, BP, etc.	Cross-sectional	Logistic and linear model, GEE	i=10746; 15427 t=12m
	Holbrook et al. 2009; Grant et al. 2008; McCarrier et al. 2009; Ralston et al. 2009	Patient	Patient	RCT	No	None	Composite score, HbA1c, BP, etc.	Cross-sectional	Multivariate model, Mixed Model, ANOVA	i=30-511 t=3-12m
	Wagner et al. 2012; McMahon et al. 2005; Ross et al. 2004	Patient	Patient	RCT	No	None	HbA1c, BP, patient activation, etc.	Longitudinal	Generalized linear mix model, mixed model	i=30-443 t=3-12m
	Smith et al. 2004; Kollmann et al. 2007	Patient	Patient	Trial	No	None	HbA1c, BP, etc.	Longitudinal	Pre-post analysis	i=10-303 t=3-6m
General IS	Venkatesh et al. 2016; Venkatesh and Sykes 2013; Venkatesh et al. 2011	Individual	Individual	Yes	Yes	None**	Satisfaction, income	Cross-sectional	SEM, PLS, OLS, hierarchical linear model	i=430-10540 t=12m-7y
	Goodhue and Thompson 1995; Ahearne et al. 2008	Individual	Individual	Both	Yes	TTF	Performance, achievement	Cross-sectional	Multivariable model, SEM	i=662;137 t=CSS; 9m
	Devaraj and Kohli 2003; Das et al. 2011; Bardhan and Thouin 2013; McCullough et al. 2010	Organization	Organization	Yes	Yes; No	None	Quality, cost, productivity, etc.	Longitudinal	Fixed effects, random effects, PDL	i=8-3401 t=36m-26y
	Bardhan et al. 2007	Project	Organization	Yes	Yes	None	Cost, quality, etc.	Cross-sectional	OLS	i=497, t=3y
	Kane and Alavi 2008	Patient and Provider	Group Level	Yes	Yes	None	Efficiency, quality	Cross-sectional	OLS, Logit	i=40, t=CSS
	Bardhan et al. 2015	Patient	Hospital	No	No	None	Readmission	Longitudinal	IV, Logit, proportional hazard, hurdle model	i=40983, t=4y
	Miller and Tucker 2011	County	County	Yes	Yes	None	Death rate	Longitudinal	Fixed effects, IV	i=2525, t=12y
	DesRoches et al. 2010; Amarasingham et al. 2009	Organization	Organization	Yes	No; yes	None	Efficiency, quality, cost	Cross-sectional	OLS, Logit	i=2952; 41 t=3y; 6m
	This study	Patient	Patient	Yes	Both	EUT	Inpatient visit, readmission, LOS, inpatient charge, ER visit, duration	Longitudinal	Fixed effects, IV, DID, NB, PCM	i=24,482 t=12 years

Abbreviations: CSS: cross-sectional survey (such that we are unable to identify study length), RCT: randomized clinical trial, BP: blood pressure, LOS: length of stay, DID: difference-in-differences, NB: negative binomial, PCM: proportional cox model, GEE: generalized estimated equations, SEM: structural equation modeling, PDL: polynomial distributed-lag model, IV: instrumental variable approach, EUT: effective use theory, VA: voluntary assignment.

** These papers have used a social network framework to explain the antecedents of use.

Table A2. Difference-in-Differences Analysis

Group		Pre-Treatment	Post-Treatment	First Difference Post-Pre
Control	Mean Std. Dev. N	0.143 0.316 121,625	0.136 0.312 68,616	-0.007** T= -4.66
Treatment	Mean Std. Dev. N	0.139 0.313 11,549	0.101 0.279 29,317	-0.038** T= -11.97
Difference in Difference		Treatment – Control		***-0.031***** ***T= -8.56***

Two-sided p-value: *p < 0.05, **p < 0.01. Mean and Std. Dev. are for ln(*in_visit*).

Table A3. Alternate Measures of Portal Use

Model	M1: use = number of interactions, after removing patients with < 2 quarters of interactions	M2: use = number of times a user has used portal messaging feature	M3: use = exclude viewing lab results
ln(Portal Interaction)	-0.050** (0.006)	-0.047** (0.006)	-0.051** (0.006)
ln(CHF Outpatient Visit)	0.022** (0.003)	0.022** (0.003)	0.022** (0.003)
ln(Non-CHF Visit)	0.015** (0.002)	0.014** (0.002)	0.014** (0.002)
Medicare Insurance	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)
Medicaid Insurance	0.006 (0.004)	0.006 (0.004)	0.006 (0.004)
Commercial Insurance	0.001 (0.005)	0.002 (0.005)	0.001 (0.005)
Elixhauser Comorbidity Index	0.021** (0.001)	0.021** (0.001)	0.021** (0.001)
Patient Age	-0.010** (0.001)	-0.011** (0.001)	-0.011** (0.001)
Patient Age^2 (in 100s)	0.011** (0.001)	0.011** (0.001)	0.011** (0.001)
Constant	0.092 (0.058)	0.119* (0.053)	0.105 (0.056)
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R-squared	0.313	0.313	0.313
N	206,625	206,625	206,625

Note: Robust standard errors in parentheses. *p < 0.05; **p < 0.01.

Table A4. Impact of Overall Portal Use on Inpatient Visits[14]

DV: ln(*in_visit*) = ln(CHF Inpatient Visit)	Model 1: Two way fixed effects with IV	Model 2: Standard DID	Model 3 Standard DID with time fixed effects	Model 4 General DID
Treat		-0.024** (0.005)	-0.020** (0.005)	
Post		0.022** (0.002)	0.007** (0.002)	
Treat*Post		-0.014* (0.006)	-0.020** (0.006)	
Portal Use	-0.047** (0.006)			-0.040** (0.006)
ln(CHF Outpatient Visit)	0.022** (0.003)	0.020** (0.003)	0.022** (0.003)	0.019** (0.003)
ln(Non-CHF Visit)	0.015** (0.002)	0.012** (0.002)	0.011** (0.002)	0.008** (0.002)
Medicare Insurance	0.001 (0.003)	0.009** (0.003)	0.009** (0.003)	0.002 (0.003)
Medicaid Insurance	0.006 (0.004)	0.015** (0.003)	0.014** (0.003)	0.006 (0.004)
Commercial Insurance	0.001 (0.005)	0.006 (0.004)	0.007* (0.003)	0.005 (0.005)
Elixhauser Comorbidity Index	0.021** (0.001)	0.028** (0.001)	0.028** (0.001)	0.020** (0.001)
Patient Age	-0.011** (0.001)	-0.002** (0.0003)	-0.001** (0.0003)	-0.010** (0.001)
Patient Age^2 (in 100s)	0.011** (0.001)	0.002** (0.0003)	0.002** (0.0003)	0.010** (0.001)
Male		0.020** (0.003)	0.019** (0.003)	
African-American		0.005 (0.003)	0.001 (0.003)	
Other Race		-0.017** (0.006)	-0.020** (0.006)	
Hispanic		0.018** (0.004)	0.014** (0.004)	
Constant	0.095 (0.058)	0.038** (0.008)	-0.071** (0.017)	0.126* (0.049)
Propensity Score Match	No	Yes	Yes	No
Individual FE	Yes	No	No	Yes
Time FE	Yes	No	Yes	Yes
R-squared	0.313	0.056	0.059	0.313
N	206,625	206,625	206,625	206,625

Note: Robust standard errors in parentheses. *p < 0.05; **p < 0.01.

[14]Portal use includes both clinical and administrative interactions.