Investing in Remote Patient Monitoring to Improve Chronic Heart Condition Outcomes

INVESTING IN REMOTE PATIENT MONITORING TO IMPROVE CHRONIC HEART CONDITION OUTCOMES

BY

WILLIAM OLIVERA-SERRANO

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ACCEPTANCE

This dissertation was prepared under the direction of the *William Olivera Serrano's* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

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Committee Co-Chairs: *Dr. Lars Mathiassen and Dr. Aaron Baird*
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Prior research has provided evidence that, on average, Remote Patient Monitoring (RPM) has a beneficial impact on hospital and patient outcomes. However, hospital investments in RPM have significant variation in effectiveness and only a few studies have examined the drivers and manifestations of these heterogeneous effects. Thus, RPM is an excellent case to better understand heterogeneity in adoption and outcomes of health IT as well as theorize the conditional nature of the effectiveness of a relational IT that connects firms, hospitals, and patients. Against this backdrop, this two-essay dissertation uses traditional econometric methods and causal machine learning to examine how different combinations of hospital and regional (county) characteristics condition RPM-related outcomes from a hospital and a patient point of view. The first essay offers a comprehensive understanding of how the outcomes associated with a relational health IT are conditional on a number of internal and external characteristics, whereas the second essay demonstrates multiple ways to identify and address the digital divide gap in outcomes across patient populations and the value of matching resources to patient subgroup needs. As a contribution to IS investment theory, the dissertation further considers the findings across the two essays to propose a conditional search mechanism that can help organizations maximize their return on IS investments. Overall, this research has important implications for policymakers deciding how to incentivize and support hospital adoption of RPM and for health care providers designing strategies for adoption and use of RPM for patients with heart failure.

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Chapter 1. Introduction

1.1. Motivation

Chronic heart conditions are the leading cause of death in the United States, as 877,000 Americans die of heart conditions each year (CDC 2022). Managing chronic heart conditions is challenging for hospitals and patients (Komajda 2015; Shah et al. 2015) as the lack of continuity of care and the constant changes to patients' health status lead to preventable hospital readmissions (Bao et al. 2020) and prolonged hospitalizations (Shirey et al. 2021).

Remote Patient Monitoring (RPM) can address the lack of continuity of care and improve outcomes (Bao et al. 2020). RPM enables real-time detection of changes to a patient's health status, which allows patients to receive specialized care and continuous monitoring within their homes instead of the hospital (Vegesna et al. 2017). From the hospital's perspective, RPM allows caregivers (i.e., nurses and support staff) the ability to receive real-time updates on patient conditions, which is helpful for chronic care management and post-surgical recovery (Health 2020). Furthermore, RPM adoption can help improve the utilization of resources, as the delegation of follow-up responsibilities with reliable data allows health care organizations to keep track of their patients without constant in-person follow-up visits (Brohman et al. 2019; Singh et al. 2011; Son et al. 2020). From a patient's perspective, RPM facilitates access to specialized resources that can provide customized care and, as a result, increases treatment adherence and effective management of chronic conditions (Pandor et al. 2013). In the context of chronic heart conditions in particular, research shows that RPM can be cost-effective for vascular and cardiac-related conditions, such as hypertension, as it can help prevent high-cost emergency department visits and longer length of hospital stays (De Guzman et al. 2022). Furthermore, research shows that when you pair RPM use with a rapid intervention team, it can potentially lower mortality at a faster rate for patients with chronic heart failure (Nakamura et al. 2014).

Unfortunately, not all hospitals that adopt RPM experience successful outcomes (Auener et al. 2021). Evidence shows that despite hospitals' investments in technologies and their efforts to train their clinicians and staff, some hospitals are simply unable to reduce their patient readmissions (McKenna et al. 2018). While RPM provides hospitals the opportunity for continuous monitoring, it is only part of the puzzle of a successful asynchronous health care configuration that requires a committed health care workforce to monitor, interpret, and respond to the information generated through RPM (Brohman et al. 2019; Nakamura et al. 2014). While prior research has provided evidence that, on average, RPM adoption helps reduce preventable hospital readmissions (Bao et al. 2020), very few studies have examined how different combinations of hospital and county characteristics complement the adoption of RPM to reduce preventable hospital readmissions for patients with chronic heart conditions. Thus, in the first essay, I ask: *For what types of hospitals and regions does adoption of RPM most reduce heart failure-related readmissions?*

At the same time, not all types of patients with chronic heart failure benefit from the use of RPM (Taylor et al. 2021). Sometimes, the most disadvantaged populations are the ones that benefit the least (Brohman et al. 2019). Therefore, while prior research has demonstrated the average impact of RPM on patient outcomes (Vegesna et al. 2017), only a few studies have examined how different hospital and county configurations fit different types of patients with chronic heart conditions. Thus, in the second essay, I ask: *Under which combination of conditions does Remote Patient Monitoring reduce patient's length of hospital stay for different types of heart failure patients?*

To address these research questions, this dissertation uses a quasi-experimental research design with a longitudinal observational approach, which is suitable to establish a cause-effect relationship between RPM and hospital and patient outcomes. In terms of methodology, I first use an econometric-driven approach to evaluate the average treatment effect of RPM. Then, I take advantage of causal machine learning to examine the heterogeneous treatment effects of RPM on hospital and patient outcomes. Causal machine learning allows researchers to relax parametric assumption restrictions and go beyond the "one-variable-at-a-time" limitations when examining treatment heterogeneity across subgroups.

Finally, leveraging the insights from both essays, I theorize the value of RPM as an IS investment (Atasoy et al. 2018; Salge et al. 2015) for hospitals and patient groups. The IS literature has proposed that IS investing is driven by search mechanisms that guide investment decisions (Salge et al. 2015). While existing IS investment search mechanisms are an excellent basis for understanding how IS investments are identified and evaluated, they often result in recommendations that are mismatched with the organization's context (Iyer and Miller 2008; Posen et al. 2018). As such, existing search mechanisms can lead to under- or over-investing in IS (Dong et al. 2021). Therefore, inspired by these limitations, I suggest the opportunity to develop a new IS investment mechanism: conditional search.

1.2. Outline of Research Essays

In Table 1.1, I provide an outline of each essay in this dissertation, followed by an overview of both essays and the research contributions.

Table 1.1. Outline of Research Essays		
	Essay 1	**Essay 2**
Focal Phenomenon	The heterogeneity of RPM impact on chronic heart condition readmissions	The heterogeneity of RPM impact on length of hospital stays for heart failure patients
Research Question	What types of hospitals and regions does adoption of RPM most reduce heart failure-related readmissions?	Under which combination of conditions does Remote Patient Monitoring reduce patient's length of hospital stay for different types of heart failure patients?
Methods	Difference-in-differences Causal forest	Causal forest subgroup analysis Policy learning
Literature	Health IT business value	Health IT digital divide
Contributions to the Literature	Offers a comprehensive understanding of how the outcomes associated with a relational health IT are conditional on a number of internal and external characteristics.	Demonstrates multiple ways to identify and address the digital divide gap in outcomes across patient populations and the value of matching resources to patient subgroup needs.
Contributions to Theory	Proposes a new IS search mechanism, "conditional search," that considers how multiple configurations impact outcomes, providing organizations with options to consider when seeking to maximizing their return on IS investments when such investments are bounded by contextual conditions.	

1.2.1. Essay 1

While prior research has provided evidence that, on average, Remote Patient Monitoring (RPM) positively impacts hospitals' health outcomes, we do not know what type of hospital and regional characteristics will most benefit outcomes when RPM is adopted in that area. Against this backdrop, I first apply a deductive, econometric-driven approach to evaluate the average treatment effect of RPM adoption on congestive heart failure readmissions. I find that, on average, RPM adoption reduces chronic heart failure readmissions. After confirming that RPM does indeed have a beneficial average effect, I extend prior work by applying an inductive, ML-driven approach to find patterns of heterogeneity in the impact of RPM. In this subsequent set of analyses, I find that hospitals with more cardiac care specialty resources and a strong background in the adoption of innovative technologies will benefit the most from the adoption of RPM. Further, as patient complexity increases, so does the ability of RPM to help reduce readmissions associated with heart failure; the absence of cardiologists in the area supporting cardiac rehabilitation diminishes RPM performance; and, hospitals in areas of high deprivation can improve their RPM adoption performance if they are members of a hospital system. The results contribute to the literature on health IT business value by extending findings beyond average effects and beyond a focus on only what occurs within a hospital, as opposed to between hospitals and patients. The results have important implications for policymakers deciding how to incentivize and support hospital adoption of RPM and managers seeking to develop health IT investment strategies that improve health care services through RPM.

1.2.2. Essay 2

The second essay examines the heterogeneous impact of RPM on the length of hospital stay for different types of patient subgroups with heart failure. Using causal forest subgroup analysis and policy learning, I find a positive impact of RPM, particularly for two types of patient groups with different needs and living in areas with different characteristics. Patient groups of higher socio-economic status are likely to maximize the impact of RPM. At the same time, I find that social associations and the presence of health care professionals and social workers can complement the use of RPM for patient groups of medium to low socio-economic status. Overall, this essay contributes to the digital divide literature by demonstrating the role of social associations and social workers in the success of RPM for patient groups of low socio-economic status.

Furthermore, the findings in this work have important implications for decision-makers by demonstrating how socio-demographic and socio-economic attributes can impact the success of RPM beyond the patient group's medical conditions.

1.2.3. Research Contributions

This dissertation argues that RPM can play a critical role in facilitating health care services and improving health outcomes for patients with heart failure, but under the right conditions. Given the complexity of this chronic disease and the diversity of hospital and patient characteristics, I advocate for the importance of examining heterogeneous treatment effects. Using econometric and causal machine learning, I find that multiple arrangements of hospital and area characteristics can facilitate the adoption and use of RPM and provide similar hospital and patient outcomes.

In terms of contributions to the literature, the first essay contributes to this growing body of work that seeks to understand how technology can play a role in emerging care configurations that extend beyond hospital beds. By focusing on a health IT that connects patients and providers, I offer a deeper understanding of how the outcomes associated with a relational (bidirectional) health IT are conditional on a number of internal (i.e., hospital) and external (i.e., regional/county) characteristics. At the same time, by examining heterogeneous treatment effects, this work explains some of the inconsistencies found in the literature on the variation in performance of health IT investments. The target journal for the first essay is *Management Science*, as the findings align with the Healthcare Management division’s goal of advancing knowledge of how to better organize innovations and the delivery of health care services. In particular, the first essay seeks to provide valuable insights relevant to health care leaders and policy makers to improve the quality of health care services through the adoption of RPM.

The second essay contributes to the digital divide literature by demonstrating that there is more than one way to address the gap in outcomes due to HIT use across patient populations. Furthermore, this work demonstrates that increasing the resources that, on average, complement RPM does not guarantee successful outcomes, but rather how those resources match the needs of each patient group for RPM. The target journal for the second essay is *Information Systems Research (ISR)*, as the findings are in line with journal's goal to advance knowledge on the effective utilization of IS by individuals, groups, and organizations to improve society. In this case, improve the quality of health care services for different patient groups with heart failure through the use of RPM.

Finally, as elaborated in Chapter 4, this dissertation draws on the findings from the two essays to make a theoretical contribution to the theory of IS investment by proposing a conditional search mechanism inspired by Resource Orchestration Theory (ROT) and configurational theorizing. The proposed search mechanism addresses the shortcomings of existing IS investment searches and explains how organizations can identify conditions for maximizing return on IS investments bounded by contextual conditions. In particular, this search mechanism considers the possibility that multiple configurations can reach similar outcomes while some configurations are not ideal for RPM investments. The theorizing explains attributes that lead to the most successful configurations. In terms of target outlet, I seek to incorporate this theorizing into an *MIS Quarterly Research Note*, as it provides theoretical insights from the analysis of rich data that expands current knowledge of IS investments search mechanisms.

Chapter 2. The Heterogeneous Impact of RPM Investments on Chronic Heart Conditions Readmissions

2.1. Introduction

In the United States (U.S.), 877,000 Americans die of heart related conditions yearly and account for $216 billion in annual health care expenditures (Benjamin et al. 2018; Yeo et al. 2023). Part of the underlying issue is that continuity of care for chronic heart conditions is difficult to manage (Shah et al. 2015), especially given frequent changes to patients' health status (Komajda 2015). The challenge of managing chronic heart disease often leads to preventable emergency hospitalizations, which cost upwards of $25 billion annually (Whitman 2016). In response, innovative approaches to managing chronic heart conditions have been sought, such as incentivizing the move from fee-for-service models to value-based models (Atasoy et al. 2018; Joynt Maddox et al. 2020). Under a fee-for-service model, the payment structure encourages a higher volume of care. For instance, research has found that 12 to 19% of procedures under fee-for-service models were not appropriate (Ray and Kusumoto 2016). In contrast, value-based health care focuses on delivering high-quality health care at the lowest possible cost (Porter and Lee 2013), in which the service is organized, performed, and paid in relation to the patient's health outcomes and experiences (Elf et al. 2017). It is especially relevant that value-based care is designed to encourage innovative approaches to care management (Zhang et al. 2016). One particular type of innovation showing promise is redesigning processes around health IT so that patients do not need as much inpatient care and can be monitored outside of the hospital.

Remote patient monitoring (RPM) enables real-time detection of changes to a patient's health status, which allows patients to receive specialized care and continuous monitoring within their homes, or skilled nursing facilities, instead of the hospital (Bao et al. 2020; Vegesna et al. 2017).

The use of RPM is critical to the success of hospital-at-home programs (Whitehead and Conley 2023), as health care organizations can support a larger volume of patients while maintaining high standards of quality care in less expensive settings (Gorbenko et al. 2023). Prior research has found that RPM adoption can help reduce the number of emergency department visits (De Guzman et al. 2022), readmissions (Bao et al. 2020), and mortality (Vandenberk and Raj 2023). But, as COVID-19 waivers that facilitate the use of RPM in hospital-at-home programs will expire in December of 2024 (Adams et al. 2023), questions remain as to whether RPM policy should remain as-is. For instance, should incentives and penalties for innovations such as RPM be applied uniformly or become more nuanced by being tailored for specific hospital types and regional conditions?

In today's world, it is crucial to consider a more nuanced policy design, as not all hospitals that adopt RPM experience successful outcomes (Auener et al. 2021; Taylor et al. 2021). Despite extensive investments in resource complementarities to support RPM adoption, some hospitals struggle to successfully apply RPM toward improving outcomes (Bhatia and Maddox 2021). While prior research has provided evidence that, on average, RPM adoption can help improve health care outcomes (Bao et al. 2020), few studies have examined what hospital and regional (e.g., county) characteristics are associated with the most impact of RPM[1]. It has been found that access to more resources does not necessarily guarantee successful outcomes (Asagbra et al. 2019), and, interestingly, that not all areas with fewer resources are doomed to have decreased health outcomes (Leung 2012; Singh et al. 2011). Research has also shown that the impact of RPM often varies depending on the conditions in which the hospital operates (Epstein et al. 2021; Muniyappa et al. 2022) and the effectiveness of resources that complement the use of RPM (Vegesna et al. 2017). However, while some studies have explored heterogeneity in specific areas, there have not been

[1] Examples of papers that considered hospital and regional characteristics on the impact of RPM: Leon et al. (2022), Chandrasekaran et al. (2023) and Mastoris et al. (2023)

efforts to systemically identify the impact of RPM across types of hospitals nor have they fully considered associated regional conditions, such as how the number of cardiologists in the region may impact RPM effectiveness. Thus, I ask: *For what types of hospitals and regions does the adoption of RPM most reduce heart failure related readmissions?*

To address this question, I first apply a deductive, econometric-driven approach (i.e., difference-in-differences) to evaluate the average treatment effect (ATE) of RPM adoption on preventable hospital readmissions. I find that, on average, RPM adoption reduces chronic heart failure readmissions, which is consistent with prior work (Bao et al. 2020; Leon et al. 2022; Vegesna et al. 2017). Then, following recent recommendations on how to best extend theory and empirical findings through the use of machine learning (Chou et al. 2023; Furnari et al. 2021; Kohli and Tan 2016), I apply an inductive, ML-driven approach (i.e., casual forest) to find patterns of heterogeneity in the impact of RPM. I find that the impact of RPM is indeed conditional on hospital and regional characteristics. This is an important finding, as policies and health IT investment strategies designed around average effects may not have as much impact as policies tailored to improve RPM performance. Specifically, I find that hospitals with more cardiac care specialty resources and a strong background in the adoption of more innovative technologies will benefit the most from the adoption of RPM.

As a result, this research makes important contributions. First, I contribute novel insights into health IT investments that extend beyond the walls of the hospital. While prior work has evaluated within hospital technologies in depth (Agarwal et al. 2010; Bhargava and Mishra 2014; Du 2015; Eftekhari et al. 2023), it is now important to consider how technology can be leveraged to enhance patient-provider care relationships in non-traditional settings (Vegesna et al. 2017; Whitehead and Conley 2023). Thus, I contribute to this growing body of work that seeks to understand how technology can play a role in emerging care configurations that extend beyond hospital beds. Second, this research identifies both average and heterogenous causal effects. This type of research design is beginning to be applied in the literature (Ayabakan et al. 2023; Wang 2022), but to my knowledge has yet to be applied to RPM evaluation and has considerable promise to contribute more nuanced findings. Finally, these findings help to explain the inconsistency of RPM performance (Auener et al. 2021; Taylor et al. 2021) and provide impetus for more nuanced policy generation and health IT investment strategies. For instance, for health care organizations that do not have the resources to continuously analyze RPM-generated data, incentives should be put in place to facilitate networks and partnerships rather than just developing an umbrella policy that subsidizes RPM investments or increases RPM-related reimbursements. Further, some of the current provider, device, and location restrictions for RPM reimbursement should likely be reconsidered in terms of the severity of chronic conditions and the resources available to complement RPM services.

In what follows, I provide more details about why it is important to both the average and heterogeneous impacts of RPM, how the research design seeks to fulfill this objective, the results from the application of difference-in-differences and causal forest methods, and discuss of implications for policy makers and health care organizations.

2.2. Literature Review

2.2.1. Reducing Readmissions for Chronic Conditions

As the largest payer for health care services in the U.S., the Centers for Medicaid and Medicare Services (CMS) created the Hospital Readmission Reduction Program (HHRP) in 2012 with the goal of reducing the number of preventable readmissions. Under this program, health care organizations receive penalties in their Medicare reimbursement payments of up to 3% based on their unplanned readmissions rates for acute myocardial infarction, chronic obstructive pulmonary disease, heart failure, pneumonia, coronary artery bypass graft surgery, elective primary total hip arthroplasty, and/or total knee arthroplasty (CMS 2012). In 2019, 82% of hospitals received financial penalties of over $566 million as a result of their readmission rates (Fontana 2018). As a result of this program, CMS has held health care organizations accountable for the discharge process (Lee et al. 2019; Zhang et al. 2016). This program also has its limitations, as the cost of reconfiguration to reduce readmissions is greater than the reimbursement penalties for some organizations, especially if they serve a low number of Medicare patients (Zhang et al. 2016). Furthermore, research has found that the impact of value-based incentive programs varies across hospital size and patient population characteristics (Qiu et al. 2022).

Thus, it is critical that patients with such chronic diseases have access to care and monitoring beyond hospital walls and receive care tailored to their unique needs (Shah et al. 2023). Toward this goal, CMS launched the Acute Hospital Care at Home program in 2020 to allow hospitals to treat patients with inpatient-level care at home to address the challenges of COVID-19. Under this program, CMS waived restrictions, such as the 24-hour requirement for onsite nursing, to allow patients to receive medical care for acute conditions at home (Gorbenko et al. 2023). Research has found that patients under this program experienced lower mortality rates and minimal complications (Adams et al. 2023), in which, large and teaching hospitals were among those who could take advantage of this program (Levine et al. 2021). Given the geographic restrictions of the program, however, patients in remote areas who would benefit from this program were the most left behind (Gorbenko et al. 2023). Concerns also remain regarding how to best scale up and sustain such programs in the long run (Adams et al. 2023; Gorbenko et al. 2023).

Health IT is one resource that can help scale and sustain care inside and outside hospitals. In general, evidence shows that health IT can help reduce the duplication of procedures (Yaraghi et al. 2015), increase referrals across organizations (Eftekhari et al. 2023), provide access to underserved populations (Singh et al. 2017), and overall, improve the delivery of health care services (Janakiraman et al. 2023; McCullough et al. 2010; Sherer et al. 2016). However, research has also found that the performance of health IT often takes time to materialize (Bhargava and Mishra 2014; Bronsoler et al. 2022), is contingent on the characteristics of the health care providers (Agarwal et al. 2010), and is heavily influenced by government policies and incentives (Hsieh et al. 2011; Lin et al. 2019). For example, with the introduction of the HITECH Act in 2009, the adoption of EHRs increased significantly from 9.0% in 2008 to 80.5% in 2015 (Adler-Milstein and Jha 2017; Lin et al. 2019). However, recent research identifies unintended consequences, including data obfuscation between providers and technology innovation vacuums (Colicchio et al. 2019). Further, given that not all health ITs are incentivized in the same manner (Adjerid et al. 2016), competition between providers also plays a big role in whether policies reach their intended outcomes (Cheng et al. 2023). Thus, given the diversity of health IT and the purpose that they serve, it is difficult to determine what conditions, policies, and incentives would work best for each type of technology.

2.2.2. Remote Patient Monitoring (RPM) Performance

In this study, I focus specifically on a technology, RPM, that can be used to help patients receive the care for chronic heart conditions[2] without needing to be an inpatient, at least when issues are nonemergent. RPM technologies are pre-programmed mobile devices, such as scales, blood

[2] Relevant chronic heart conditions: Heart failure, coronary artery and vascular disease, heart rhythm disorders, and structural heart disease. Additional information on types of chronic heart conditions: https://my.clevelandclinic.org/health/diseases/21493-cardiovascular-disease

pressure devices, and pulse oximeters, that send vital health data to health care providers (Health 2020). RPM facilitates the delegation of monitoring patients without constant in-person follow-up visits (Brohman et al. 2019; Singh et al. 2011; Son et al. 2020). In particular, RPM allows caregivers (i.e., nurses and support staff) the ability to receive real-time updates on patient conditions, which is especially helpful for chronic care management (Shah et al. 2023; Vandenberk and Raj 2023).

RPM is especially relevant to chronic heart condition management because it can capture and transmit key information such as heart rate, cardiac rhythm, respiration rate, oxygen saturation, blood pressure, as well as information on physical activity, sleep quality, and body weight that allows clinical teams to have a comprehensive picture of the patient on an ongoing basis (Serrano et al. 2023; Shah et al. 2023). Research shows that RPM can be cost-effective for vascular and cardiac-related conditions, such as hypertension, as it can help prevent high-cost emergency department visits (De Guzman et al. 2022) and reduce mortality (Vandenberk and Raj 2023). Furthermore, RPM can be as effective as traditional outpatient cardiac rehabilitation centers for post-discharge monitoring tasks for patients with heart failure (Nakayama et al. 2020). Even further, research shows that when RPM is paired with a rapid intervention team, it can potentially lower mortality for patients with chronic heart failure (Nakamura et al. 2014). Overall, researchers agree that, on average, RPM improves clinical outcomes of patients with chronic heart conditions (Ding et al. 2020; Pandor et al. 2013), such as by reducing readmissions, length of stay, and emergency department visits (Bao et al. 2020).

However, the performance of relational health IT services such as RPM that technologically connect patients and providers located in different places remains highly heterogeneous (Peters et al. 2015). For instance, for similar technologies, including video-based telehealth and patient portals (Baird et al. 2022; Sun et al. 2020; Thompson et al. 2020), research shows that performance will rely on specialty doctors, nurses, and technologists capabilities (Steinhauser et al. 2020; Turner et al. 2022). Research also shows that adopting relational health IT can sometimes create new problems for health care organizations (Zhou et al. 2023), such as increasing the workload of specialists (Bavafa et al. 2018). Similar to other health IT, hospital financial resources (Agarwal et al. 2010; Grossi et al. 2021; McCullough et al. 2010), network affiliations (Chen et al. 2019; Li et al. 2022; Venkatesh et al. 2011), academic affiliations (McCullough et al. 2010; Paul et al. 2020), types of ownership (Greenwood et al. 2017) and technology infrastructure (Du 2015; Mishra et al. 2022) are likely to impact health IT performance.

Evidence also shows that despite hospitals' investments in technologies and their efforts to train their clinicians and staff, some hospitals are simply unable to reduce their patient readmissions (Bhatia and Maddox 2021; McKenna et al. 2018). As Taylor et al. (2021) noted in their systematic literature review, RPM interventions are complex, and their outcomes exhibit high variation across patients. For instance, recent research states that the heterogeneity of RPM performance can be strongly determined by factors outside of the hospitals, such as socioeconomic status and lack of key resources in the area where they operate (Mastoris et al. 2023; Shah et al. 2022). Further, while in theory RPM can substitute for the lack of cardiac rehabilitation services and specialized cardiology resources (Ruan et al. 2023), in reality, interpreting RPM data can be complex (Leon et al. 2022). Not all organizations and regions have the resources to act on RPM-generated data (Brahmbhatt et al. 2022). The impact of such technologies is ultimately dependent on the needs of the population and the availability of health care services that will compete with or complement organizational capabilities (Li et al. 2020; Rajan et al. 2013; Steinhauser et al. 2020).

In sum, while RPM performance can lead to the improvement of health care outcomes, in reality, many organizations' RPM workflows are fractured and inefficient, triggering additional use of front-line services and increasing the rate of positive false alarms (Auener et al. 2021; Harvey and Seiler 2022; Leon et al. 2022; Serrano et al. 2023). Further, RPM performance may decrease over time as the support resources and financial incentives that facilitate RPM get discontinued (Koehler et al. 2020). Evidence also shows that underusing services such as RPM could limit access to traditional care, and overuse could increase spending and make RPM-generated data unmanageable (Harris et al. 2024). Therefore, in order to optimize the impact of RPM, we need to consider which types of hospitals and regions will benefit the most from the adoption of RPM.

2.3. Research Design

2.3.1. Research Setting

To examine the impact of RPM adoption on chronic heart condition related readmissions, I apply a quasi-experimental research design to longitudinal, observational data. This design is suitable because I seek to establish a cause-and-effect relationship between RPM and hospital readmissions. I construct a hospital-year dataset using the American Hospital Association's (AHA) annual survey and the associated IT supplement for 2016 through 2019. The survey is sent to every CEO of the Association's hospitals in the U.S. and has been used in previous studies to examine the impact of technology adoption on hospital organizations (Daniel 2018; Karahanna et al. 2019; Yaraghi et al. 2015). The internal consistency, construct validity, and criterion validity of the items measured in the survey as adoption indicators have performed well on the reliability and validity index (Everson et al. 2014). Furthermore, I complement the AHA hospital data with public datasets from the Centers for Medicare and Medicaid Services (CMS) Compare files and the Hospital Cost

Report Information System (HCRIS) (see Table 2.1 for details). To capture the context of the area in which the hospitals operate, I also complement the dataset with county characteristics from the Area Health Resource Files (AHRF), County Health Rankings (CHR), the Federal Communications Commission (FCC), and the University of Wisconsin-Madison Neighborhood Atlas.

2.3.2. Variable Selection

For the dependent variable, I use the heart failure readmission rates posted from the CMS public files to operationalize hospital readmission rates for those with chronic heart conditions (Table 2.1). This variable measures the percentage of re-hospitalizations within 30 days after discharge when originally admitted for a heart failure diagnosis, and it is an important component of the HRRP calculation (Zhang et al. 2016). On average, in the sample, 21% percent of the discharges with a heart failure diagnosis were readmitted to the hospital within 30 days.

The primary independent variable of interest is RPM adoption. To measure RPM adoption, I use the measures from the AHA and IT supplement surveys that indicate whether hospitals have RPM technologies for the years of 2017 and 2018.

For the other independent variables of interest used as both control variables and to assess heterogeneity, I use data from the AHA and HCRIS files to operationalize the *hospital characteristics*, which are described in more detail next.

Table 2.1. Data Sources and Operationalization of Constructs			
Construct	**Indicator**	**Operationalization**	**Source**
Hospital Outcomes	Heart failure readmissions	Heart failure readmission rates	CMS (2016-2019)
Hospital RPM Adoption	RPM technology	Hospital adoption of RPM for general use and for chronic care management	AHA IT (2016-2019)
Hospital Characteristics	Cardiac care resources	Number of beds in the coronary care unit	HCRIS (2016-2019)
	Health IT resources	Saidin index of health ITs adopted	AHA IT (2016-2019)
	Workforce resources	Total number of beds	AHA (2016-2019)
		Total number of doctors	AHA (2016-2019)
		Total number of registered nurses	AHA (2016-2019)
		Hospital system membership	AHA (2016-2019)
		Teaching hospital	AHA (2016-2019)
	Financial resources	Hospital revenue	HCRIS (2016-2019)
	Patient health complexity	Case mix index	HCRIS (2016-2019)
		Medicare discharges	AHA (2016-2019)
Population Characteristics (per U.S. County)	Cardiac care resources	Ratio of population to cardiologists	AHRF (2016-2019)
	Health it resources	Number of hospitals with RPM	AHA IT (2016-2019)
		Broadband access rate	FCC (2016-2019)
	Workforce resources	Cardiac rehabilitation hospital concentration (HHI)	AHA (2016-2019)
	Financial resources	Area deprivation index	Neighborhood Atlas (2016-2019)
	Population health complexity	Number of heart failure cases	CMS (2016-2019)

For a *hospital's cardiac care resources*, I operationalize the construct by measuring the number of beds in a coronary care unit. Coronary care units specialize in caring for patients with cardiac conditions requiring continuous monitoring. These units require medical providers and staff trained in cardiac care and require a higher staff-to-patient ratio compared to other hospital units (Gidwani and Kini 2013; Wongvibulsin et al. 2021). Therefore, as the number of beds in the coronary care unit increases, so will the number of specialized cardiac care resources (Loughran et al. 2017).

To operationalize a *hospital's health IT resources*, I calculate a health IT Saidin index to measure the health IT capabilities (Spetz and Maiuro 2004). The Saidin index is calculated by considering the sum of health technologies available in the hospital weighted against the percentage of hospitals that do not possess the technology. Therefore, the Saidin index will be higher for hospitals that adopt technologies less common relative to the technology adopted by other hospitals. In this context, the Saidin index allows us to quantify the number of technologies and the level of health IT innovation that compose a hospital's health IT capabilities. Similar studies have leveraged the Saidin index to operationalize digital advantage (Karahanna et al. 2019) or health IT capabilities relative to other hospitals (Angst et al. 2017). To calculate the Saidin index, I calculate the weight of a given technology across hospitals $\alpha_{k,t}$ as follows: $\alpha_{k,t} = 1 - \left(\frac{1}{N_t}\right) \sum_{i=1}^{N_t} T_{i,k,t}$ where for each hospital i, I index each technology by k=1,…,K, with t as the year and N_i as the number of hospitals in year t. $T_{i,k,t}$ will equal 1 if hospital i has the technology in year t, or 0 otherwise. I then use the weights to calculate the Saidin index for hospital i as follows: $S_{i,t} = \sum_{i=1}^{N_t} \alpha_{k,t}\, T_{i,k,t}$. In line with similar studies, I consider the 47 reported technologies that appeared in all the years of the sample.

To operationalize the *hospital's workforce and financial resources*, I leverage the hospital's total number of beds, total number of doctors, total number of nurses, whether the hospital is part of a system, whether a hospital is a teaching hospital, and the hospital revenue. These variables are often included as controls in research that examine the impact of health IT innovations on health care outcomes (Baird et al. 2022; Cheng et al. 2023; Fan et al. 2023; Karahanna et al. 2019).

To operationalize a *hospital's patient health complexity*, I leverage the case mix index and Medicare discharges. Both measures serve as indicators to describe the complexity and severity of the hospital's patient population, and they are often used to control in similar types of studies (Atasoy et al. 2018; Du 2015; Zhang et al. 2016).

Regarding the *population (county) characteristics*[3], I operationalize *county cardiac care resources* as the ratio of the population count to cardiologists in the county in thousands. For

3 We also considered looking at county characteristics by HRR. We re-estimate of the population characteristics by HRR in the robustness check.

example, a value of eight indicates that for every eight thousand people in the population, there is one cardiologist to support them. A higher value for this ratio is correlated with medical professional shortage areas (Bilazarian 2022; Brown et al. 2011).

Regarding *county health IT resources*, I use the broadband access in each county and the number of hospitals in the area with RPM capabilities (Du 2015; Mishra et al. 2022).

In terms of *county health care workforce resources*, I use the concentration of cardiac care rehabilitation hospitals in the area. To measure the concentration, I calculate the Herfindahl-Hirschman Index (HHI) as a measure of market concentration to determine the level of competition for these services in the area. In which: $HHI = \sum_{i=1}^{N}(MS_i)^2$, where MS_i is the market share of firm i in a market with N number of firms.[4] A lower value of HHI is associated with a higher degree of competition (Chang and Gurbaxani 2013). The use of HHI as a measure to indicate the concentration of resources has been highly used in the literature (Gong et al. 2023; Guo et al. 2023; Lu et al. 2018).

Finally, I include area deprivation and the number of heart failure cases in the county as indicators for *county financial resources* and *county population health complexity*, respectively (Ahmad et al. 2019; Hatef et al. 2021; Zhang and Ram 2020).

2.3.3. Identification Strategy

In terms of the identification strategy, I first apply a difference-in-differences approach to examine the *average treatment effect on the treated* (ATT) of RPM adoption on hospital's heart failure readmissions. To mitigate concerns of potential endogeneity and self-selection bias, I select treatment and control groups prior to the implementation period using propensity score matching

[4] The HHI calculation uses county FIPS to measure concentration. We understand that HRR is also used to calculate HHI in similar research. However, HRR can cross state lines and has less granularity compared to counties. We re-estimate the models using HRR to calculate HHI as a robustness check later in the paper.

(PSM) (Rosenbaum and Rubin 1983). I use a logistic regression to predict the propensity scores and then leverage a nearest neighbor matching algorithm with replacement and a caliper of 0.02 standard deviations from the propensity score to select matching controls. As a result of the matching procedure, I ended up with 128 hospitals in the first implementation wave (2017), 129 hospitals in the second implementation wave (2018), and 243 hospitals in the control group with no significant differences between the treatment and control groups.[5]

Using the matched sample, I conduct the DiD analysis with the following model:

$$Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 p_{it} + \beta_3 (T_{it} * p_{it}) + \mu_i + \vartheta_t + \varepsilon_{it}$$

β_1 is the effect from the treatment group, β_2 represents post-treatment time periods, β_3 is the treatment effect. I include hospital-fixed effects (μ_i) to address any time-invariant hospital heterogeneity and time-fixed effects to address time trends (ϑ_t). I adopt robust standard errors to correct for potential heteroskedasticity (Wooldridge 2010) and cluster the standard errors by county (FIPS) to account for variables aggregated at the county level.

After estimating the ATT of RPM on heart failure readmissions, I estimate *heterogeneous treatment effects* (HTEs) using the causal forest with an honest tree algorithm (Wager and Athey 2018). The causal forest decomposes the ATE within the sample into subgroups of local treatment effects by learning the data without parametric assumption restrictions. The honesty feature helps reduce bias by using different subsamples to either construct the tree or make predictions (Wager and Athey 2018), a necessary feature for a valid statistical inference (Dandl et al. 2024). In health care, research has used causal forests to find heterogeneity in ED wait time across hospital groups (Wang 2022) and to learn what patient populations to target for medical treatments (Marafino et

[5] We also considered using coarsened exact matching (CEM) to match the dataset and reduce group differences (Iacus et al. 2012). While we find similar outcomes in the ATE calculations, it limited the ability to examine heterogeneous treatment effects given the limited sample size after matching.

al. 2020). The causal forest method has also been suggested as an effective way to determine non-linear and interacting effects in business research (Chou et al. 2023; Hu 2023).

Under traditional regression models, adding interactions means making assumptions associated with linearity or functional form. However, as more interactions are included, there is no guarantee that the assumptions made are correct (Athey and Imbens 2019; Chou et al. 2023). Causal forest methods, on the other hand, do not make linearity assumptions. These methods focus on identifying average differences in outcomes between treated and not treated hospitals within each leaf of the tree (Wager and Athey 2018). The model splits the sample based on "Where can it do a split that will produce the biggest difference in treatment effects, but which will still give an accurate estimate of the effect?" It provides an average effect for specific subgroups, which will help predict individual effects for future observations with the same characteristics (Wager and Athey 2018).

Initially, I explore (X_i, Y_i) as independent samples that form regression tree and W_i as the treatment variable for the adoption of RPM. Following Wager and Athey (2018), I recursively split the feature space until I have a number of leaves L that contain only a few training samples. I then evaluate the prediction $\hat{\mu}(x)$, given a test point x, by identifying the leaf L(x) containing x and setting: $\hat{\mu}(x) = \frac{1}{|\{i: X_i \in L(x)\}|} \sum_{\{X_i \in L(x)\}} Y_i$

The leaf L(x) is small enough that the responses Y_i are roughly identically distributed. I estimate the treatment effect for any $X_i \in L(x)$ as:

$$\hat{\tau}(x) = \frac{1}{|\{i : W_i = 1, X_i \in L\}|} \sum_{\{i: W_i = 1, X_i \in L\}} Y_i - \frac{1}{|\{i : W_i = 0, X_i \in L\}|} \sum_{\{i: W_i = 0, X_i \in L\}} Y_i.$$

Finally, I generate an ensemble of B causal trees as a causal forest by aggregating the predictions by averaging them: $\hat{\tau}(x) = B^{-1} \sum_{b=1}^{B} \hat{\tau}_b (x)$.

Causal forests require overlap and unconfoundedness assumptions. I use the matched dataset from the initial matching procedure to address the overlap assumption and include all relevant hospital and county characteristics as controls for the model. To address the unconfoundedness assumptions, I follow an orthogonalization approach using the "R learner" inspired by Robinson's transformation (Robinson 1988). In this stage, I first train a separate regression forest and perform out-of-bag predictions to calculate estimates of propensity scores ($e(x) = E[W|X=x]$) and marginal outcomes ($m(x) = E[Y|X=x$). I then use the residual of the treatment and outcome to train the causal forest on the residuals. This orthogonalization stage is essential to obtain accurate treatment effects in a quasi-experimental research design (Athey and Imbens 2019).

I also cluster the standard errors by county to account for hospitals with the same county characteristics. By doing so, the subsampling process accounts for entire clusters instead of individual hospitals. To ensure the resulting groups are of equal size for meaningful interpretations, I set the forest samples per cluster to be equal to the smallest cluster. As a result of the clustering procedure, the standard errors from the ATE calculations become cluster robust. Finally, I standardize the covariates for modeling and easier interpretation.

Given the panel structure of the dataset, I use the first difference causal forest (FDCF) approach recommended by Wang (2022). Under this approach, I use the pre-implementation period covariates to examine the HTE. For the dependent variable, I first calculate the difference in HF readmission rates of each hospital in their pre- and post-implementation periods and then, I apply the causal forest approach and observe the doubly robust estimates of the ATE, average treatment on the treated (ATT), and the overlap-weighted ATE, used when there is a concern with the overlap assumption (Li et al. 2018). Finally, to identify the HTEs, I project the treatment effect across the hospital and county characteristics using the best linear projection approach (Chernozhukov et al.

2018; Wager and Athey 2018). I then replicate the projections across low and high value subgroups of each of the hospital characteristics. I do so by splitting the sample across high and low values with respect to the median for continuous variables, except for the number of cardiac care unit beds. Given that less than half of the sample of hospitals have cardiac care unit beds, I split the sample into hospitals with and without cardiac care unit beds. For the binary variables, I split the sample of hospitals based on whether or not they are system members or teaching hospitals. As a result, I can examine heterogeneity across hospital groups with similar characteristics.

2.4. Empirical Results

I first provide the descriptive statistics of the overall sample. Next, I describe the average and heterogeneous treatment effect analyses to show the impact of RPM on HF readmissions.

2.4.1. Descriptive Statistics

Table 2.2 presents the descriptive statistics for the sample in the pre-treatment periods. I removed any hospital with missing data from the variables of interest across the years of the sample. As described in the previous section, I balance the covariates between the treatment and control groups using propensity score matching (PSM). Appendix 2.7 demonstrates that there are no significant differences in the treatment between the treatment and control groups. As a result, I ended up with 128 hospitals in the first implementation wave (2017), 129 hospitals in the second implementation wave (2018), and 243 hospitals that did not implement RPM in the sample period.

Table 2.2. Descriptive Statistics						
Variable	**Count**	**Mean**	**Std**	**P25**	**Median**	**P75**
Hospital Variables						
Heart failure readmission rate	2000	21.91	1.67	20.78	21.9	22.9
Number of beds	2000	228.25	178.89	100	187	301
Number of cardiac care unit beds	2000	3.4	10.86	0	0	0
Number of Medicare discharges	2000	5,053.92	3,948.91	2178	4,208	6,685.2
Number of doctors	2000	57.59	162.31	1	17	48
Number of nurses	2000	643.94	589.67	276	472	809
System membership	2000	0.76	0.43	0	1	1
Teaching hospital	2000	0.06	0.23	0	0	1
Revenue (in millions)	2000	111.71	149.1	20.31	59.21	139.15
Case mix index	2000	1.57	0.22	1.43	1.6	1.7
Saidin index	2000	6.99	1.72	5.86	7	8.2
Accountable care organizations (ACOs)	2000	0.43	0.49	0	0	1
Population Variables						
Cardiac rehabilitation hospital concentration (HHI)	2000	0.49	0.38	0.2	0.3	1.0
Number of hospitals with RPM	2000	2.51	4.24	0.0	1.0	3.0
Broadband access rate	2000	84.41	6.07	81.1	85.1	88.7
Number of heart failure cases	2000	360.75	741.44	37.0	123	360
Population to cardiologist ratio (in thousands)	2000	5,547.94	17,636.39	10.74	18.07	37.44
Area deprivation index	2000	56.24	18.12	47.5	59	69
Note: The majority of the hospitals in the matched sample are non teaching hospital, members of a hospital network, without cardiac care unit beds. The majority of the health care organizations that adopt RPM in the sample area ACOs. Matching on ACOs would significantly reduce the sample size and the ability to examine heterogeneous treatment effects. Therefore, I exclude matching on ACOs in the main analysis. In the robustness test, I match and include ACOs in the analysis.						

2.4.2. Average Treatment Effects

I use a difference-in-differences approach to examine the ATT[6] of the adoption of RPM on HF readmissions. Table 2.3 illustrates the results of the difference in differences models. Model 1 includes both hospital and time fixed effects. Model 2 and Model 3 add hospital and population characteristics described in the previous section in addition to the fixed effects. Model 4 includes both hospital and county characteristics. To control for differences in the variance as a result of intragroup correlation (Berry Jaeker and Tucker 2017; Wang 2022), I include robust standard errors clustered by FIPS. The coefficients across all models are statistically significant, which indicates that, on average, the adoption of RPM reduces HF readmission rates. In the final model, I find that

[6] The Difference-in-Differences estimates result in "average treatment effects on the treated" because we selected a control group to resemble the treatment group and we obtain the estimates from the group that was treated instead of a population that could have been treated. See Ryan et al. (2015).

on average, RPM adoption reduces heart failure readmission rates by 0.346, which indicates that on average, hospitals adopting RPM reduce their readmission rates by 1.59%.

Table 2.3. ATT of RPM Adoption on Heart Failure Readmissions				
	Model 1	**Model 2**	**Model 3**	**Model 4**
RPM Adoption	-0.320 (0.102)***	-0.302 (0.107)***	-0.343 (0.101) ***	-0.346 (0.111)***
Hospital Characteristics	×	✓	×	✓
Population Characteristics	×	×	✓	✓
Hospital Fixed Effects	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓
Observations	2000	2000	2000	2000
Adjusted R^2	0.615	0.616	0.623	0.623

Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Robust standard errors clustered by FIPS reported in parentheses.
Model (1) does not include hospital or population characteristics. Models (2) includes hospital characteristics. Model (3) includes population characteristics. Model (4) includes both hospital and patient characteristics.

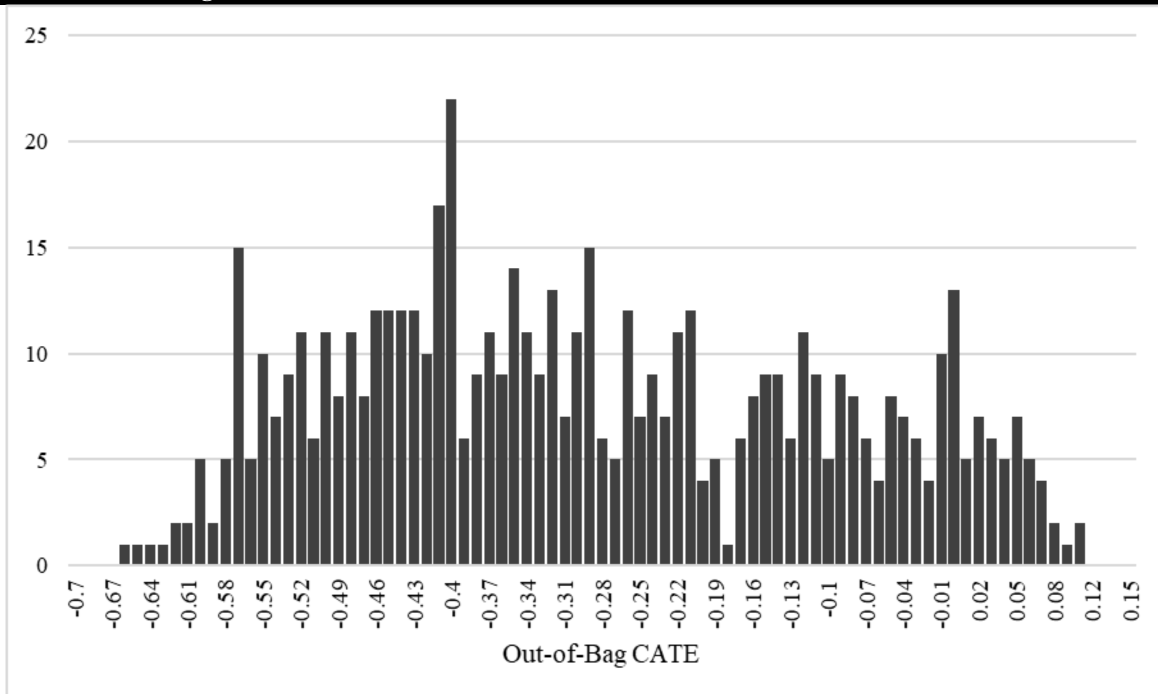
2.4.3. Heterogeneous Treatment Effects

Next, I examine the heterogeneous treatment effects (HTEs) on heart failure readmissions across the different hospital and region characteristics. First, using the causal forest method, I calculate the ATE, the ATT, and the overlap-weighted ATE of the impact of RPM on readmissions. I do this to verify that the HTE approach is consistent with the previous estimation strategy. Table 2.4 presents the results. All coefficients are significant, which indicates that, on average, RPM adoption helps to decrease HF readmissions. I note that while the coefficients are slightly different from the difference-in-differences model due to the different modeling assumptions, they are not statistically significant from each other, which provides validity to the main model. In Figure 2.1, I plot the out-of-bag conditional ATE (CATE) to visualize the heterogeneity of the impact of RPM adoption on HF readmissions.

Table 2.4. RPM Impact of HF Readmissions via Causal Forest		
	Estimate	**Standard Error**
Average Treatment Effect	-0.278*	0.117
Average Treatment Effect on the Treated	-0.339**	0.122
Overlap-weighted Average Treatment Effect	-0.261*	0.125

Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001;
Robust standard errors reported in parentheses.

Figure 2.1. Out-of-bag CATE



To understand the tendencies of heterogeneity across the variables of interest on the impact of RPM on heart failure readmissions, I estimate the best linear projection of CATEs for the selected variables (Athey and Imbens 2019; Wang 2022). I standardize the coefficients for interpretation and report cluster robust standard errors. Table 2.5 describes the results of the model. First, the results indicate that a higher number of cardiac care unit beds (-0.473, $p<0.05$) and Saidin index (-0.323, $p<0.05$) will significantly increase the impact of RPM adoption on reducing heart failure readmissions. Further, a higher case mix index will marginally (-0.323, $p<0.10$) increase the impact of RPM adoption on reducing heart failure readmissions.

Table 2.5. Best linear Projection of CATE		
	Estimate	**Standard Error**
Hospital Characteristics		
Number of beds	0.306	(0.349)
Number of cardiac care unit beds	-0.473**	(0.182)
Number of Medicare discharges	0.036	(0.303)
Number of doctors	0.045	(0.145)
Number of nurses	-0.150	(0.345)
System membership	-0.109	(0.135)
Teaching hospital	0.041	(0.134)
Revenue	-0.094	(0.202)
Case mix index	-0.321+	(0.164)
Saidin index	-0.323*	(0.125)
Population Characteristics		
Cardiac rehabilitation hospital concentration (HHI)	0.163	(0.125)
Number of hospitals with RPM	0.040	(0.242)
Broadband access	0.236	(0.150)
Number of heart failure cases	-0.017	(0.257)
Population to cardiologist ratio	-0.113	(0.109)
Area deprivation index	-0.112	(0.136)
Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Cluster heteroskedastic robust standard errors reported in parentheses; Variable coefficients are standardized		

Next, I examine whether the treatment effect varies across the hospital characteristics. Table 2.6 presents the results. I find that hospitals will reduce their heart failure readmission rates when they adopt RPM and have a higher than the median: number of cardiac care unit beds (-1.018, p<0.001), number of beds (-0.542, p<0.01), Medicare discharges (-0.624, p<0.001), doctors (-0.291, p<0.10), nurses (-0.440, p<0.01), revenue (-0.668, p<0.001), case mix index (-0.531, p<0.01), Saidin (-0.795 p<0.001), are system members (-0.434, p<0.01), and are teaching hospitals (-1.023, p<0.001).

Except for hospital beds and cardiac care unit beds, all other subgroups experience significant heterogeneity. For hospitals with a higher number of Medicare discharges, I find that a higher number of cardiac care unit beds will increase the impact of RPM adoption on reducing HF readmission rates.

Table 2.6. Best linear Projection of CATE across Hospital Characteristics			
		Low | 0 Value	**High | 1 Value**
CATE by number of beds		-0.071 (0.159)	-0.542 (0.170)**
CATE by number of cardiac care unit beds		-0.148 (0.126)	-1.018 (0.275)***
CATE by Medicare discharges		0.012 (0.166)	-0.624 (0.159)***
Heterogeneity	H: Number of cardiac care unit beds		-0.387 (0.198)+
CATE by number of doctors		-0.250 (0.167)	-0.291 (0.166)+
Heterogeneity	H: Number of cardiac care unit beds		-0.633 (0.234)**
CATE by number of nurses		-0.131 (0.165)	-0.440 (0.163)**
Heterogeneity	H: Number of beds		0.609 (0.342)+
	H: Case mix index		-0.479 (0.265)+
	H: Number of cardiac care unit beds		-0.387 (0.200)+
CATE by system membership		0.145 (0.241)	-0.434 (0.132)**
Heterogeneity	H: Number of cardiac care unit beds		-0.356 (0.184)+
	H: Case mix index		-0.484 (0.180)**
	H: Saidin		-0.289 (0.128)*
	C: Area deprivation index		-0.365 (0.154)*
	C: Broadband access		0.274 (0.155)+
CATE by teaching hospital		-0.233 (0.122)+	-1.023 (0.301)***
Heterogeneity	H: Saidin	-0.324 (0.130)*	
	H: Number of cardiac care unit beds	-0.547 (0.209)**	
CATE by revenue		0.017 (0.162)	-0.668 (0.163)***
CATE by case mix index		-0.071 (0.162)	-0.531(0.166)**
Heterogeneity	H: Number of cardiac care unit beds		-0.399 (0.231)+
	C: Broadband access		0.547 (0.272)*
CATE by Saidin		0.126 (0.169)	-0.795 (0.154)***
Heterogeneity	H: Number of cardiac care unit beds		-0.594 (0.326)+

Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001;
Robust standard errors clustered by county reported in parentheses; H: Hospital variable C: County variable; Only significant variables presented for visualization; HTE variable coefficients are standardized for interpretation. For binary variables low value equals 0, and high value equals 1.

For hospitals with a higher number of doctors, I find that a higher number of cardiac care unit beds increase the impact of RPM adoption on reducing HF readmission rates.

For hospitals with a higher number of nurses, I find that a higher number of cardiac care unit beds and case mix index increase the impact of RPM adoption on reducing HF readmission rates. On the other hand, I find that hospitals with a higher number of beds will marginally decrease the impact of RPM adoption on reducing HF readmission rates.

For hospitals that are members of a hospital system, I find that a higher number of cardiac care unit beds, case mix index, and Saidin index increase the impact of RPM adoption on reducing HF readmission rates. Furthermore, if the hospitals that are members of a hospital system operate in areas of high deprivation, it increases the impact of RPM adoption on reducing HF readmission rates. At the same time, for hospitals that operate in areas with higher broadband access, it decreases the impact of RPM adoption on reducing HF readmission rates.

While I find that, on average, teaching hospitals significantly benefit from RPM adoption, non-teaching hospitals can also benefit from RPM adoption to reduce HF readmission rates if they have a higher Saidin index and a higher number of cardiac care unit beds.

For hospitals with a higher case mix index, I find that a higher number of cardiac care unit beds will increase the impact of RPM adoption on reducing HF readmission rates. However, if the hospitals operate in areas with higher broadband access, it decreases the impact of RPM adoption on reducing HF readmission rates. Finally, for hospitals with a higher Saidin index, I find that a higher number of cardiac care unit beds will increase the impact of RPM adoption on reducing HF readmission rates.

Next, I examine whether the treatment effect varies across the population characteristics. Table 2.7 presents the results. I find that hospitals will reduce their heart failure readmission rates when they adopt RPM if they operate in areas that have a higher than the median: number of hospitals with RPM (-0.637, $p<0.05$), number of heart failure cases (-0.421, $p<0.05$), area deprivation index (-0.442, $p<0.01$). At the same time, I find that hospitals will reduce their heart failure readmission rates when they adopt RPM if they operate in areas that have a lower than the median: cardiac rehabilitation hospital concentration (-0.572, $p<0.01$), broadband access (-0.345, $p<0.05$), and population to cardiologist ratio (-0.298, $p<0.10$)

Table 2.7. Best linear Projection of CATE across Population Characteristics			
		Low Value	**High Value**
CATE by cardiac rehabilitation hospital concentration (HHI)		-0.572 (0.192)**	-0.196 (0.155)
CATE by number of hospitals with RPM		-0.219 (0.127)+	-0.637 (0.259)*
Heterogeneity	H: Saidin	-0.372 (0.132)**	
	H: Number of cardiac care unit beds	-0.566 (0.193)**	
CATE by broadband access		-0.345 (0.165)*	-0.192 (0.166)
Heterogeneity	H: Case mix index	-0.477 (0.235)*	
	H: Number of cardiac care unit beds	-0.567 (0.228)*	
CATE by heart failure cases		-0.193 (0.151)	-0.421 (0.184)*
CATE by population to cardiologist ratio		-0.298 (0.171)+	-0.239 (0.160)
CATE by area deprivation index		-0.140 (0.166)	-0.442 (0.164)**
Heterogeneity	H: Number of cardiac care unit beds		-0.503 (0.228)*
	H: Case mix index		-0.444 (0.244)+
	H: System membership		-0.483 (0.219)*
	C: Population to cardiologist ratio		-0.246 (0.123)*
	C: Cardiac rehabilitation hospital concentration (HHI)		0.353 (0.193)+

Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001;
Cluster heteroskedastic robust standard errors reported in parentheses; H: Hospital variable C: County variable; Only significant variables presented for visualization; HTE variable coefficients are standardized for interpretation. For binary variables low value equals 0, and high value equals 1.

I find significant heterogeneity in the number of hospitals with RPM, broadband access, and area deprivation index subgroups. While I find that, on average, hospitals that operate in areas where with neighboring hospitals have already implemented RPM significantly benefit from RPM adoption, hospitals that operate in areas with a few to none neighboring hospitals with RPM capabilities can also benefit from RPM adoption to reduce HF readmission rates if they have a higher Saidin index and a higher number of cardiac care unit beds.

For hospitals that operate in areas of lower broadband availability, I find that a higher number of cardiac care unit beds and case mix index will increase the impact of RPM adoption on reducing HF readmission rates.

Finally, for hospitals that operate in areas with higher area deprivation indexes, I find that a higher number of cardiac care unit beds, case mix index, and system membership will increase the impact of RPM adoption on reducing HF readmission rates. Furthermore, if the area also has a higher population-to-cardiologist ratio, the impact of RPM adoption on reducing HF readmission rates will increase. On the other hand, if the area also has a higher concentration with cardiac rehabilitation services, it decreases the impact of RPM adoption on reducing HF readmission rates.

In sum, the examination of the CATE across subgroups allowed us to uncover different patterns of heterogeneity on the impact of RPM on reducing readmissions. While the impact of RPM across each of the subgroups is consistent with the expectations from the literature, I find how the impact of these characteristics can vary depending on the area where the hospital operates, which may explain some of the contrasting findings in the literature. I further elaborate on the implications in the discussion section.

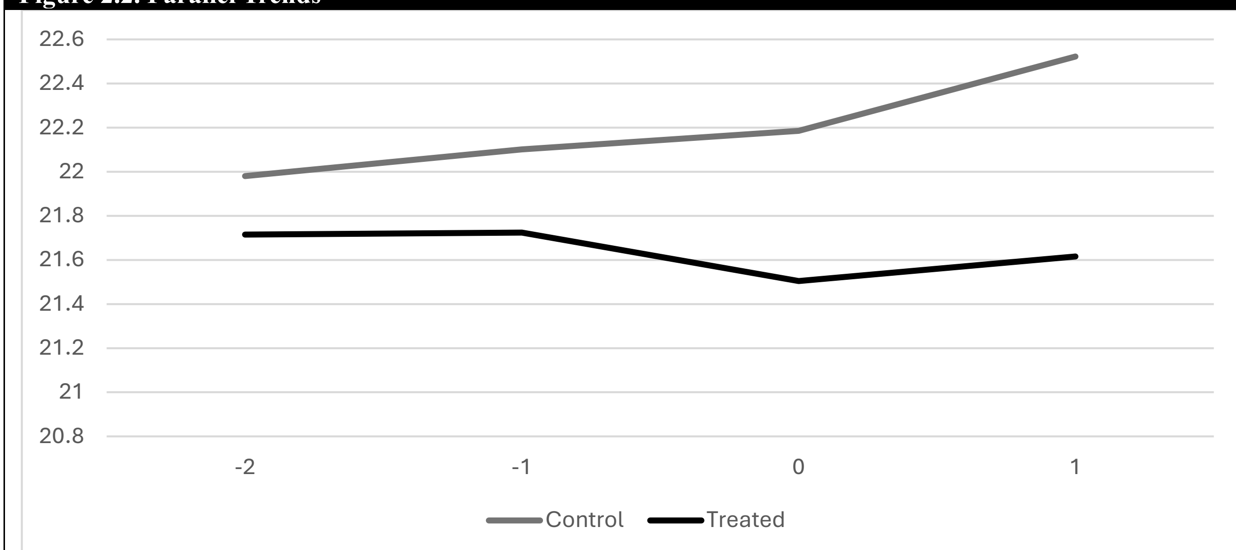
2.4.4. Robustness Checks

I conduct a series of robustness checks to provide validity to the analysis. First, given the staggered adoption of RPM across the sample, there are concerns that variation in treatment timing will fail to produce interpretable treatment effects under a two-way fixed effects specification (Goodman-Bacon 2021). Therefore, I replicate the analysis using a difference-in-differences approach with multiple periods (Callaway and Sant'Anna 2021) to account for the staggered implementation of RPM across 2017 and 2018. This approach can help mitigate concerns about contemporaneous trends that could confound the treatment effect of RPM on readmissions. As in previous models, the robust standard errors are clustered by FIPS. Table 2.8 shows the results of the robustness check, in which I find that, on average, RPM adoption significantly reduces HF readmission rates by -0.368 ($p<0.05$). When the treatment effect is grouped by the 2017 and 2018 implementation waves, the average impact of RPM adoption on HF readmission is significant at -0.373 ($p<0.05$) and -0.363 ($p<0.05$), respectively. In terms of the dynamic effects, during the adoption year and one year after, the results show that RPM adoption reduces heart failure readmissions by -0.321 ($p<0.05$) and -0.421 ($p<0.05$), respectively. The results are not statistically significant two years after the adoption of RPM. The results are similar and not statistically significantly different from those presented in the main analysis, which validates the initial model specification. In terms of parallel trends, the analysis shows that one year before the adoption of RPM, the differences between the treated and control groups were not significant. Furthermore, Figure 2.2 helps us visualize the parallel trends before the staggered implementation of RPM and after the implementation period.

Table 2.8. ATT of RPM Adoption on Heart Failure Readmissions

	ATT	Std. Error	95% Confidence Interval
Overall RPM Implementation	-0.3677	0.1115	[-0.5865, -0.1495]*
2017 Wave	-0.3729	0.1377	[-0.6827, -0.0630]*
2018 Wave	-0.3632	0.1461	[-0.6919, -0.0344]*
Event Time			
-1	-0.1250	0.1239	[-0.4281, 0.1781]
0	-0.3206	0.0843	[-0.5267, -0.1144]*
1	-0.4211	0.1363	[-0.7543, -0.0878]*
2	-0.3616	0.2083	[-0.8711, 0.1479]

Figure 2.2. Parallel Trends



Given the staggered adoption of RPM and the heterogeneity in the treatment effect, the estimated adoption leads may exhibit a pre-treatment dip in outcomes, creating a mistaken perception of a violation of parallel trends (Sun and Abraham 2021). When estimating the difference-in-differences model under a two-way fixed effects approach, I calculate the outcome after removing time and hospital characteristics using unit and time fixed effects. However, this approach also creates a residualized treatment indicator, which may lead to issues interpreting the treatment under the presence of HTEs (Sun and Abraham 2021). Therefore, as a robustness test, I leverage a two-stage adoption approach proposed by Butts and Gardner (2021) in which I estimate unit and time fixed effects separately so I don't residualize the treatment indicators. In the first stage, I estimate the model excluding treated units with the unit and time fixed effects, as well as the hospital and county characteristics. In the second stage, I use the untreated outcome from the first stage and subtract it from the observed outcome, which will be the outcome of treated observations. Finally, regressing the outcome of the treatment observations on the treatment indicator will give an unbiased estimate of the treatment effect. The results described in Table 2.9 show that the impact of RPM adoption is statistically significant for both implementation groups, confirming the impact of RPM adoption on HF readmissions across the two implementation cycles.

Table 2.9. Butts and Gardner (2021) Two Stage Difference-in-Differences

	Estimate	**Standard Error**
2017 RPM Adoption	-0.226*	0.106
2018 RPM Adoption	-0.177*	0.076

Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001;
Number of Observations: 2000; Adjusted R2: 0.008

To check that the estimates are not a consequence of spurious correlation, I conduct a time falsification test (Rishika et al. 2013), in which I designate a placebo implementation period one year earlier than the actual implementation (i.e., set 2017 as the implementation period for the 2018 implementation group). As presented in Table 2.10, the coefficients are not statistically significant, suggesting that the model is correctly specified.

Table 2.10. Time Falsification of RPM Adoption on Heart Failure Readmissions				
	Model 1	**Model 2**	**Model 3**	**Model 4**
RPM Adoption	0.118 (0.085)	0.116 (0.086)	-0.088 (0.085)	-0.083 (0.091)
Hospital Characteristics	×	✓	×	✓
Population Characteristics	×	×	✓	✓
Hospital Fixed Effects	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓
Observations	2000	2000	2000	2000
Adjusted R^2	0.612	0.614	0.620	0.621
Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Robust standard errors clustered by FIPS reported in parentheses. Model (1) does not include hospital or population characteristics. Models (2) includes hospital characteristics. Model (3) includes population characteristics. Model (4) includes both hospital and patient characteristics.				

Next, the model specification operates under an unconfoundeness assumption. While I include all available covariates cited in the literature as controls in the models, concerns remain about the potential impact of unobservable confounders. Therefore, I conduct a sensitivity analysis to establish how sensitive the analysis is to an unobserved confounder (Cinelli and Hazlett 2020). The sensitivity analysis allows us to determine how strong an observed confounder would need to be to change the main outcomes of the analysis. The results presented in Table 2.11 show that the robustness value (RV) of RPM adoption is 8.5%. This indicates that if the unobserved confounders do not explain at least 8.5% of the residual variance of both the treatment and outcome, it would not be sufficiently strong to bring down the estimated effect of RPM adoption (Cinelli and Hazlett 2020). The robustness test for testing the null hypothesis equals 3.7%, which indicates unobserved confounders do not explain at least 3.7% of the residual variance of the treatment and outcome are not strong enough to make the estimate not statistically significant. Finally, the partial R^2 test shows that in the extreme case the confounders were to explain 100% of the residual variance of the outcome, they would need to explain at least 0.8% of the residual variance of the treatment to take away the effect of RPM adoption. To evaluate the potential impact of an unobserved confounder, I include the number of beds in the hospital as a benchmark. Both indicators for the benchmark are well below the RV of 8.5% and the partial R2 of 0.8%, which means that confounders as strong as the number of beds cannot explain away the RPM adoption estimate.

Furthermore, even in an extreme case in which an unobservable confounder, similar to the benchmark, explains all residual variation of the outcome and is strongly associated with the treatment, it would not be able to take away the effect of RPM adoption. Through this sensitivity test, I can reduce the concern that the analysis may be biased due to an unobserved confounder.

Table 2.11. Sensitivity Analysis of RPM Adoption on Heart Failure Readmissions						
Treatment	**Estimate**	**Std. Error**	**t-value**	$R^2_{Y\sim D\|X}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
RPM Adoption	-0.366	0.107	-3.409	0.8%	8.5%	3.7%
Note: df=1485; Number of beds: $R^2_{Y\sim Z\|X,D}$= .01%, $R^2_{D\sim Z\|X}$=.2%						

To address concerns that the coefficients may be biased due to the limited number of time periods (Hill et al. 2020), I use a random effect model to estimate the impact of RPM adoption. As presented in Table 2.12, the RPM adoption coefficients are statistically significant. Furthermore, the coefficient is not statistically different from the main analysis, which suggests that the coefficients are not biased when including hospital fixed effects.

Table 2.12 Random Effects of RPM Adoption on Heart Failure Readmissions	
	Random Effects Model
RPM Adoption	-0.314 (0.075)***
Hospital Characteristics	✓
Population Characteristics	✓
Observations	2000
Adjusted R^2	0.084

Next, I conduct a falsification test with alternative samples to validate the robustness of the analysis. In the first model, I exclude hospitals penalized over 2% on their reimbursement payments due to their excess readmissions of chronic conditions under the Hospital Readmissions Reduction Program (HRRP). This falsification test allows us to remove hospitals that are strongly incentivized to reduce chronic condition readmissions in the same time window in which I evaluate the impact of RPM adoption on HF readmissions. In the second model, I include an indicator that determines which hospitals have accountable care organization (ACO) contracts. As expected, the majority of the health care organizations that adopt RPM in the sample area are part of an ACO. Therefore, I was unable to include them in the matched dataset as it would significantly reduce the sample size. In the third model, I create an indicator for hospitals that operate in states with RPM reimbursement laws for Medicaid and private payers. Most of the hospitals that adopt RPM operate in states with specific RPM reimbursement laws. In the fourth model, I replicate the analysis by grouping the number of heart failure cases, the number of hospitals with RPM, and the concentration of cardiac rehabilitation hospitals (HHI) by hospital referral region instead of the county FIPS. Hospital referral regions are formed by grouping zip codes together based on the referral patterns for tertiary care for Medicare beneficiaries. Across the alternative sample models, I replicated the propensity score matching approach to guarantee that the covariates were not statistically significantly different across the treatment and control groups in the pre-treatment periods. As presented in Table 2.13, the coefficients of RPM adoption remain statistically significant, suggesting that the impact of RPM adoption on HF readmissions is robust across the alternative samples.

Table 2.13. ATT of RPM Adoption on Heart Failure Readmissions using an Alternative Sample

	Model 1	Model 2	Model 3	Model 4
RPM Adoption	-0.297 (0.114)***	-0.182 (0.109)*	- 0.355 (0.116)***	-0.365 (0.107)***
Hospital Characteristics	✓	✓	✓	✓
Population Characteristics	✓	✓	✓	✓
Hospital Fixed Effects	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓
Observations	1,608	1,812	1,696	2,000
Adjusted R^2	0.610	0.640	0.642	0.624

Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Robust standard errors clustered by FIPS reported in parentheses. Model (1) excludes hospitals penalized 2% on their reimbursement payments. Models (2) matches and controls for ACOs. Model (3) matches and controls for hospitals in states with RPM Medicaid and private payer's reimbursement laws.

Next, I conduct a falsification test with alternative outcomes. I use the log-transformed variables of emergency department visits (Table 2.14) and total hip/ knee arthroplasty readmissions (Table 2.15) as alternative outcomes. I re-estimate the treatment effect by testing the impact of RPM on overall emergency department visits and non-chronic related readmissions. In Tables 2.14 and 2.15 the coefficients are not statistically significant, which provides evidence that supports that the impact of RPM centers around chronic related readmissions.

Table 2.14. ATT of RPM Adoption on the Natural Log of Emergency Department Visits				
	Model 1	**Model 2**	**Model 3**	**Model 4**
RPM Adoption	-0.051 (0.054)	-0.047 (0.048)	-0.043 (0.050)	-0.041 (0.048)
Hospital Characteristics	×	✓	×	✓
Population Characteristics	×	×	✓	✓
Hospital Fixed Effects	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓
Observations	2180	2180	2180	2180
Adjusted R^2	0.919	0.919	0.919	0.919
Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Robust standard errors clustered by FIPS reported in parentheses. Model (1) does not include hospital or population characteristics. Models (2) includes hospital characteristics. Model (3) includes population characteristics. Model (4) includes both hospital and patient characteristics.				

Table 2.15. ATT of RPM Adoption on Total Hip/Knee Arthroplasty Readmissions				
	Model 1	**Model 2**	**Model 3**	**Model 4**
RPM Adoption	-0.012 (0.009)	-0.008 (0.009)	-0.010 (0.009)	-0.004 (0.009)
Hospital Characteristics	×	✓	×	✓
Population Characteristics	×	×	✓	✓
Hospital Fixed Effects	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓
Observations	1712	1712	1712	1712
Adjusted R^2	0.591	0.591	0.594	0.596
Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Robust standard errors clustered by FIPS reported in parentheses. Model (1) does not include hospital or population characteristics. Models (2) includes hospital characteristics. Model (3) includes population characteristics. Model (4) includes both hospital and patient characteristics.				

To validate the HTEs, I examine the forest goodness of fit by running a calibration test that computes the best linear fit of the estimand using the forest prediction on the held out data following the recommendations of Chernozhukov et al. (2018). Table 2.16 describes the results. The result shows that the mean of the predicted treatment effect is statistically significant and close to 1, indicating that the mean forest prediction is correct. At the same time, the differential forest prediction was statistically significant and close to 1, which indicates that I can significantly detect the overall heterogeneity of the model.

Table 2.16. Forest Calibration		
	Estimate	**Standard Error**
Mean Forest Prediction	1.033*	0.463
Differential Forest Prediction	1.346*	0.669
Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Predictions calculated on held-out data with mean forest prediction as regressors Standard errors are cluster by FIPS and heteroskedasticity-robust.		

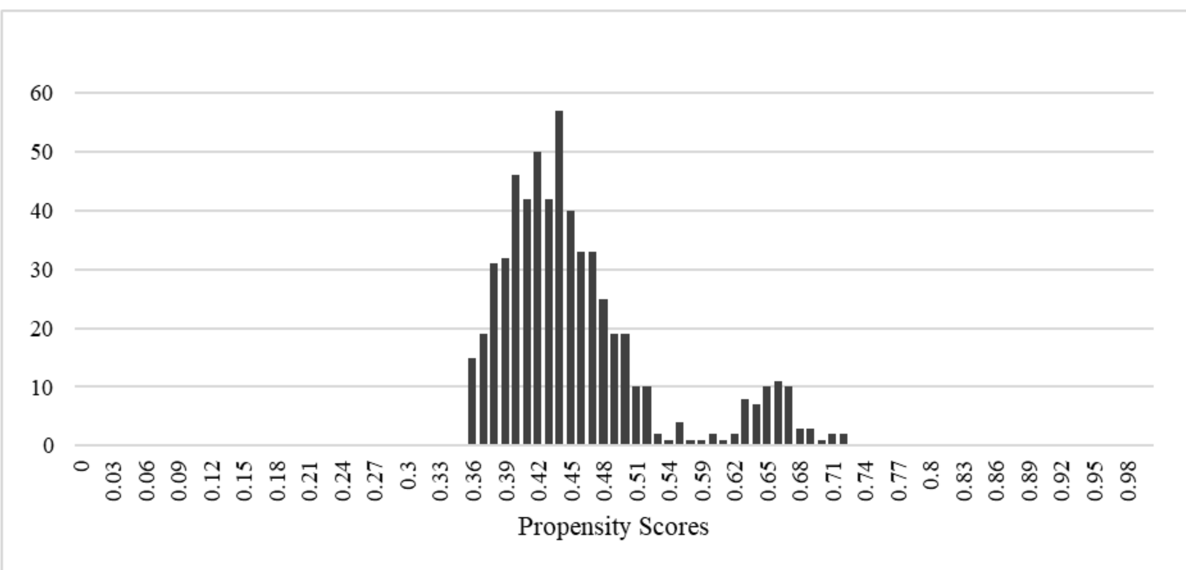
I further validate the presence of heterogeneity by performing a heuristic test of heterogeneity by grouping the observations into high and low CATE (Athey and Wager 2019). I split and compared the observations into halves and terciles groups. As presented in Table 2.17, I find a significant difference in CATE across the groups, implying heterogeneity in the treatment effect.

Table 2.17. CATE Heterogeneity Test

	Estimate	**Standard Error**
1/3 CATE	-0.445*	0.198
3/3 CATE	0.123	0.204
Difference	-0.568*	
1/2 CATE	-0.513***	0.150
2/2 CATE	-0.092	0.168
Difference	-0.422+	
Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001;		

Next, the causal forest relies on the overlap assumption that requires a positive probability of treatment for each covariate, where the treatment status of each hospital is not determined based on its covariates. To address the overlap assumption, I match the dataset based on the covariates during the pre-treatment period and plot the propensity scores (Figure 2.3) to validate that the scores are not close to one or zero.

Figure 2.3. Histogram of Estimated Propensity Scores Based on Covariates

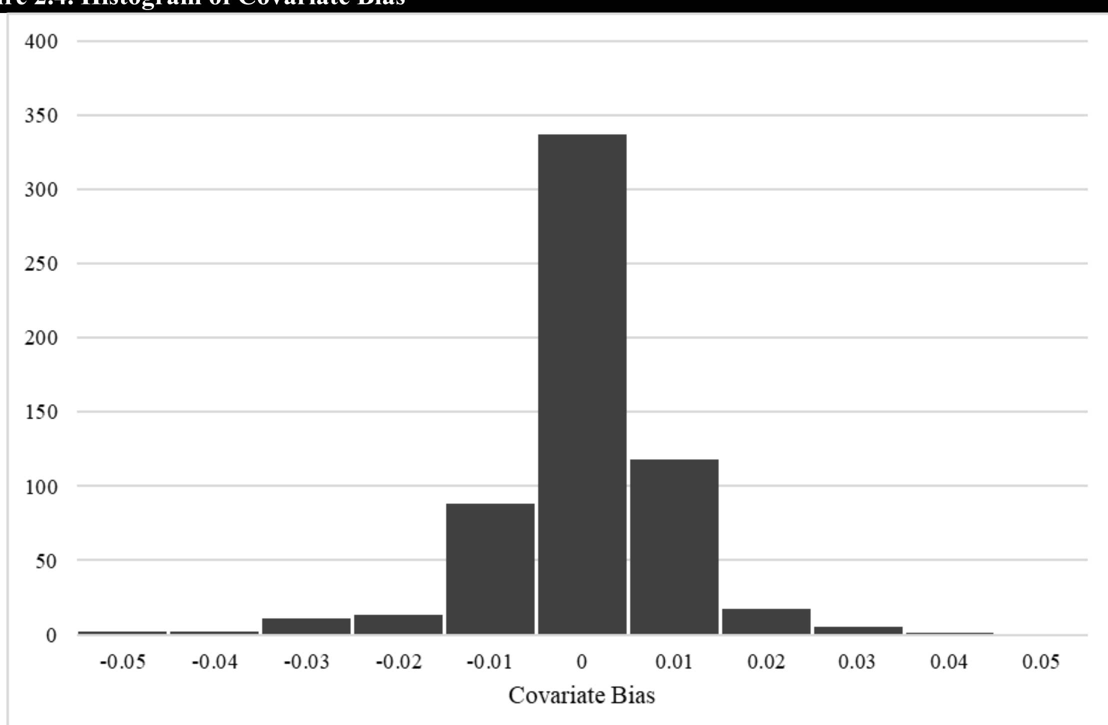


Finally, to address the concern that the estimator is biased due to the pre-treatment variables associated with both the treatment and potential outcomes, I measure the sparsity of the product of the propensity score of pre-treatment variables associated with the treatment and the propensity score of pre-treatment variables associated with the outcomes that result in bias (Athey et al. 2017):

$$B = \left(E\left[Y_i^{obs}\middle|W_i = 1\right] - E\left[Y_i^{obs}\middle|W_i = 0\right] - t = \frac{1}{p(1-p)}\right) E[b(X_i)]$$

And with the bias function of: $b(x) = (e(x) - p) * (p(\mu(0,x) - \mu_0) + (1-p)(\mu(1,x) - \mu_1)$. As a result, the bias is proportional to the covariance of the propensity score and the weighted average of the conditional expectations of the outcomes. The bias function measures the contribution to the overall bias coming from each of the covariates (Athey et al. 2017). I plot the outcomes in Figure 2.4 scaled by the standard deviation of the outcome, and I observe that results do not have a large variance compared to the difference in the average outcomes by treatment effects.

Figure 2.4. Histogram of Covariate Bias



2.5. Discussion

In this study, I investigate the impact of RPM on chronic heart disease-related readmissions and identify the types of hospitals and regions for which RPM has the most significant impact. I contribute in a number of ways. Contextually, I contribute by focusing on a health IT that connects patient and providers, which similar to other recent work focusing on telehealth impacts (Ayabakan et al. 2023; Bao et al. 2020; Bardhan et al. 2015; Li et al. 2020). I offer a deeper understanding of how the outcomes associated with a relational (bidirectional) health IT are conditional on a number of internal (i.e., hospital) and external (i.e., regional/county) characteristics. Methodologically, I apply an approach (difference-in-differences followed by causal forest analysis) that identifies an ATE and then delves deeply into heterogeneity, which has been applied in the literature to other policy considerations (e.g., Medicaid expansion, Wang (2022)), but, to my knowledge, has yet to be applied to RPM outcome evaluation. This is an important contribution as I show that developing policy focused solely on average effects may miss the opportunity to improve RPM performance through development of more nuanced policies. For instance, RPM investments may be more impactful in areas that either have more cardiologists or, in areas lacking cardiologists, where the local hospital(s) are system members. Thus, policies that simply incentivize RPM investment may be more effective if they either incentivize the complements specified here or structure the RPM investment incentives so that areas with the most potential benefit are the most highly incentivized. Finally, the findings could help explain the inconsistency of RPM performance found in prior studies (Auener et al. 2021; Taylor et al. 2021). In what follows, I discuss the implications of the findings in more detail.

2.5.1. Research Implications

While prior research has provided evidence that, on average, RPM adoption helps reduce preventable hospital readmissions, existing research has not identified the combination of hospital and county characteristics that will maximize the impact of RPM adoption on chronic heart condition readmissions. This research finds that hospitals with a higher number of cardiac care unit beds and a higher Saidin index will maximize the impact of RPM on reducing chronic heart readmissions. The presence of strong cardiac care and technology resources allows hospitals to monitor patients outside of hospital settings and increase the quality of care they provide. Taken together, this implies that organizations considering the implementation of RPM should review the composition of their workforce and current technology investments to conditionally determine how whether RPM would effectively fit into current resource configurations.

Second, in line with prior research, I find that hospitals with greater size, workforce, and financial resources can generate more benefits from RPM (Agarwal et al. 2010; Grossi et al. 2021; McCullough et al. 2010). However, I also find that the impact of RPM for those organizations increases if there is a need for RPM, given the complexity of their patient population. This has important implications because, given the severity of their chronic conditions, the alternative of an RPM treatment would imply an increased number of hospital visits and potentially longer hospital stays. On the other hand, if hospitals serve a population with lower severity of chronic conditions, then the impact of RPM may not necessarily improve readmission rates, and thus may either be unnecessary or should be more limited in size and scope.

Third, I find that if the population size significantly outweighs specialty cardiologists in the area where hospitals operate, the impact of RPM adoption will diminish. RPM performance is linked to the capability to interpret and act from RPM-generated data within and outside the hospital. While RPM adopters have the critical task and make decisions from RPM-generated data, some of those tasks may be better performed by other health care organizations in the county that are better suited, such as home health agencies. For instance, research suggests that organizations follow a decentralized system to analyze their RPM generated data through the use of their system network or third-party services to remove the strain on local resources (Bhatia and Maddox 2021; Harvey and Seiler 2022; Makutonin et al. 2023). Therefore, in contrast with prior literature that states that more competing resources outside the organization can lead to lower health IT outcomes (Cheng et al. 2023), I find the opposite, as the presence of cardiologists in the county that can provide ad hoc services can complement the impact of RPM adoption for the focal hospital.

Finally, while prior literature has noted the difficulty for organizations in areas of high deprivation to improve their health care services as a result of health IT adoption (Epstein et al. 2021; Muniyappa et al. 2022), this research shows that hospitals in areas of deprivation can improve the impact of RPM adoption if they are members of a hospital system. As organizations in areas of deprivation lack specialty resources to analyze and interpret the information, they can leverage their membership in a hospital system to help improve the impact of their RPM adoption on performance. While it is too early to tell, this finding may be consistent with recent events, including the Kaiser purchase of Geisinger, as while Geisinger is very innovative, Kaiser brings a breadth and depth of managed care knowledge that may end up encouraging use of tools such as RPM over a higher volume of in-person visits (Pearl 2023). Therefore, my findings imply that policymakers could improve health care services equity via policies that facilitate the ability for health care organizations in areas of deprivation to build partnerships and join hospital system networks that would enable to improve health care services based on their investment in RPM.

In sum, this research contributes to the literature that seeks to understand how technology can play a role in emerging care configurations that extend beyond hospital beds. While prior work has evaluated the impact of technologies under traditional hospital settings in depth (Angst et al. 2010; Bhargava and Mishra 2014; Du 2015; Eftekhari et al. 2023), very few have considered the impact of technologies under non-traditional hospital settings and how these technologies can be leveraged to enhance patient-provider care relationships (Vegesna et al. 2017; Whitehead and Conley 2023). By focusing on a health IT that connects patients and providers, this work offers a deeper understanding of how the outcomes associated with a relational (bidirectional) health IT are conditional on a number of internal and external characteristics. Finally, by examining heterogeneous treatment effects and going beyond identifying conditions that work on average, this work explains some of the inconsistencies found in the literature on the variation in RPM performance and identifies the hospital and regional characteristics that allow organizations to maximize the impact of RPM on chronic heart condition readmissions.

2.5.2. Practical Implications

In terms of practical implications, I contribute to the literature by focusing on a health IT that connects patient and providers, which is similar to other recent work focusing on telehealth impacts (Ayabakan et al. 2023; Bao et al. 2020; Bardhan et al. 2015; Li et al. 2020). I offer a deeper understanding of how the outcomes associated with a relational (bidirectional) health IT are conditional on a number of internal (i.e., hospital) and external (i.e., regional/county) characteristics.

The findings indicate that, on average, RPM adoption reduces heart failure readmissions and that in agreement with similar research, hospitals with a greater size, workforce, and financial resources can generate more benefits from RPM (Agarwal et al. 2010; Grossi et al. 2021; McCullough et al. 2010). However, I find evidence that simply having a greater size and workforce does not guarantee success. As the result shows, only when hospital organizations have resources tied to cardiac care is when it positively complements RPM.

The results also show that the hospitals that maximize their investment in RPM have a high-complexity patient population with strong cardiac care and technology capabilities. This suggests that organizations considering the implementation of RPM should first review the needs of their patient population because, given the severity of their chronic conditions, the alternative of an RPM treatment would imply an increased number of hospital visits and potentially longer hospital stays. On the other hand, if hospitals serve a population with lower severity of chronic conditions, then the impact of RPM may not necessarily improve readmission rates, and thus may either be unnecessary or should be more limited in size and scope. At the same time, hospitals should review the composition of their workforce and current technology investments to conditionally determine whether RPM would effectively fit into current resource configurations.

RPM performance is linked to the capability to interpret and act from RPM-generated data within and outside the hospital. While RPM adopters have the critical task and make decisions from RPM-generated data, some of those tasks may be better performed by other health care organizations in the county that are better suited, such as home health agencies. For instance, research suggests that organizations follow a decentralized system to analyze their RPM generated data through the use of their system network or third-party services to remove the strain on local resources (Bhatia and Maddox 2021; Harvey and Seiler 2022; Makutonin et al. 2023). Therefore, in contrast with prior literature that states that more competing resources outside the organization can lead to lower health IT outcomes (Cheng et al. 2023), I find the opposite, as the presence of cardiac rehabilitation services in the county can provide ad hoc services that can complement the impact of RPM adoption for the focal hospital.

Furthermore, while prior literature has noted the difficulty for organizations in areas of high deprivation to improve their health care services as a result of health IT adoption (Epstein et al. 2021; Muniyappa et al. 2022), this research shows that hospitals in areas of deprivation can improve the impact of RPM adoption if they are members of a hospital system. As organizations in areas of deprivation lack specialty resources to analyze and interpret the information, they can leverage their membership in a hospital system to help maximize the impact of their RPM adoption. Finally, this finding could help explain the inconsistency of RPM performance found in prior studies (Auener et al. 2021; Taylor et al. 2021).

2.5.3. Policy Implications

This research suggests that developing policy focused solely on average effects may miss the opportunity to maximize the impact of RPM through the development of more nuanced policies. For instance, RPM investments may be more impactful in areas in need, with organizations that can provide services complementary to RPM, and for hospitals that are members of a system in areas of deprivation. Thus, policies that simply incentivize RPM investment may be more effective if they either also incentivize the complements specified here or structure the RPM investment incentives in a way that areas with the most potential benefit are the most highly incentivized.

The findings also highlight the role a hospital system can play in maximizing RPM performance in areas of deprivation. For instance, policymakers could improve health care services equity via policies that facilitate the ability of health care organizations in areas of deprivation to build partnerships and join hospital system networks that would enable them to maximize their investment in RPM and improve health care services.

In sum, this work suggests that some hospitals are better prepared than others to implement RPM. Recognizing the heterogeneity of the impact of RPM, decision-makers should consider, given the area in which their hospital operates, what characteristics of their hospital they should invest in first, before adopting RPM. At the same time, a hospital system can identify which of its hospitals could benefit the most from RPM adoption and how its networks may be able to support the analysis of RPM-generated data if those hospitals have limited resources. Finally, as health emergency waivers put in place during COVID-19 to facilitate RPM use are set to expire, policymakers should consider that to create a sustainable environment for RPM to work, they recognize what drives the heterogeneity within each hospital and region. Under current policies, access to RPM is based on where the person lives, their provider, and who pays for the services rather than the patients who stand to benefit the most (Harris et al. 2024). Furthermore, simply increasing reimbursement has sparked an increase in billing fraud related to RPM services (HHS 2023). Therefore, this research suggests that future policies should go beyond subsidies and reimbursements of PRM tasks, and facilitate resources that complement RPM workflows given the heterogeneity of conditions across each of the areas the hospitals serve that will help improve the delivery of health care services.

2.5.4. Limitations and Future Research

This work has a few limitations. First, the variable to identify RPM adoption only identifies if a hospital adopts any type of RPM but does not specify the type of RPM they adopt. Prior studies have made the same assumption in examining the health IT impact on hospital performance (Daniel 2018; Vest et al. 2022; Vest et al. 2019; Zhao et al. 2019). To my knowledge, there is not a public data source that captures the specific type of RPM use on a national sample of U.S. hospitals. Second, the causal forest method relies on a strong assumption of unconfoundeness and overlap. While the methods and inclusion of relevant covariates from the literature increase the validity of the analysis, I recognize there is still a potential concern of unobservable confounders that may bias the results. Despite the limitations, this work has important implications and avenues for future research. For example, future research could follow a similar research design and methodological approach to examine the heterogeneous impact of other health IT or other types of hospital investments or process changes.

2.6. Conclusion

In closing, I argue that RPM can play an active role in value-based models and help improve health care services. By examining the heterogeneity of RPM adoption across hospital and county characteristics, I provide a holistic understanding of RPM performance and illustrate the conditions in which health care organizations can maximize the impact of RPM to improve their health care services.

2.7. Appendix

Covariate Comparison Between Treatment and Control Groups					
	Control		**Treatment**		
Variable	**Mean**	**Std**	**Mean**	**Std**	**Δ P-value**
Hospital Variables					
Number of beds	234.99	181.42	214.94	158.54	0.145
Number of cardiac care unit beds	3.3	9.63	3.8	12.37	0.591
Number of Medicare discharges	4867.09	3772.87	4967.52	3676.79	0.741
Number of doctors	44.81	151.59	55.13	133.51	0.371
Number of nurses	577.16	501.11	634.41	556.08	0.192
System membership	0.73	0.45	0.75	0.43	0.476
Teaching hospital	0.04	0.19	0.07	0.25	0.107
Revenue (in millions)	102.77	127.05	93.29	127.38	0.364
Case mix index	1.57	0.22	1.57	0.22	0.825
Saidin index	6.52	1.45	6.46	1.55	0.633
Accountable care organizations (ACOs)	0.15	0.36	0.53	0.50	0.001
County Variables					
Cardiac rehabilitation hospital concentration (HHI)	0.46	0.39	0.51	0.37	0.093
Number of hospitals with RPM	1.1	2.33	1.02	2.37	0.66
Broadband access	84.39	6.12	84.45	5.92	0.895
Number of heart failure cases	183.41	278.12	190.94	249.74	0.725
Population to cardiologist ratio (in thousands)	5,552.32	18,170.98	5,469.45	16,612.87	0.951
Area deprivation index	55.91	18.78	57.22	17.87	0.378

Note: The majority of the health care organizations that adopt RPM in the sample area ACOs. Matching on ACOs would significantly reduce the sample size and the ability to examine heterogeneous treatment effects. Therefore, I exclude matching on ACOs in the main analysis. In the robustness test, I match and include ACOs in the analysis.

Chapter 3. Reducing Disparities in Length of Hospital Stay for Patients with Heart Failure Through RPM Investments.

3.1. Introduction

Heart failure is the leading cause of cardiovascular hospitalization in the United States (Shirey et al. 2021) and places a large resource and financial burden on the health care system (King-Dailey et al. 2022). From a patient perspective, it can cost an average of $15,000 per inpatient visit (Kilgore et al. 2017; Shafie et al. 2018), and prolonged heart failure hospitalizations are often associated with an increase in the likelihood of hospital-acquired infections and inpatient medical complications (Khan et al. 2015; Siddique et al. 2021). Unfortunately, deciding the optimal time to discharge a patient goes beyond clinical factors (Almashrafi et al. 2016), as health care providers need to ensure that patient's living conditions will allow them to continue with their treatment after heart failure event (Rethy et al. 2021; Segar et al. 2022).

Research suggests that as part of hospital-at-home programs, Remote Patient Monitoring (RPM) can facilitate the treatment of heart failure patients after discharge by allowing providers to monitor patients from their home, instead of the hospital (Bao et al. 2020). Research shows that RPM facilitates customized care and increases treatment adherence (Pandor et al. 2013). Unfortunately, not all patients with heart failure who use RPM see a positive impact on their health outcomes (Auener et al. 2021; Taylor et al. 2021). From a digital divide lens, research shows that the impact of technology use, similar to RPM, can vary depending on socio-demographic and socio-economic status (Agarwal et al. 2009; Lythreatis et al. 2022; Song et al. 2021). At the same time, research shows that minority populations tend to avoid relying on technologies such as RPM due to the lack of access of supporting resources (Ancker et al. 2017). While current research digital divide literature has done an excellent job at identifying patient groups that struggle to maximize their use of health IT (Saeed and Masters 2021) and the conditions that facilitate or hinder health IT performance for those populations (El-Rashidy et al. 2021), very few have considered there might be multiple ways to reduce the digital divide, as not all patients have the same needs for the technology or have the same access to resources that complement the technologies. Therefore, simply identifying what conditions and resources complement RPM on average might not be the best solution across all contexts.

In sum, while the literature has provided evidence that, on average, RPM reduces patients' length of hospital stay (Bao et al. 2020; Ding et al. 2020; Pandor et al. 2013), very few have considered the heterogeneity of patient populations in their needs and the resources available to them to complement RPM to manage their heart failure. Thus, I ask: *Under which combination of conditions does Remote Patient Monitoring reduce patient's length of hospital stay for different types of heart failure patients?*

To address this research question, I construct a longitudinal dataset of patient groups using data from the Healthcare Cost and Utilization Project (HCUP) State Emergency Department Databases (SEDD) for Arizona, Florida, Maryland, and Wisconsin to determine the interactions between patients and health care providers for 2017, 2018, 2019, and 2020. Through the use of the causal forest subgroup analysis, I find that RPM can help two different types of patient groups to reduce patient's length of hospital stay. The first group consists of younger patients with a high severity of their medical condition and live in areas with limited health care resources. The second group consists of older patients with moderate severity of comorbidities who live in areas with a strong presence of health care and social care resources tied to cardiac services. Through policy learning, I find that people living in areas of higher socio-economic status are likely to maximize the impact of RPM. However, the findings also show that social associations and the presence of health care professionals and social workers can complement the use of RPM for those of medium to low socio-economic status.

Taken together, the findings have very important implications. First, this work provides evidence that RPM can help reduce patient's length of hospital stay for two different types of populations with different needs and living in areas with different characteristics. These insights can help policy makers understand how RPM can help different types of patients with heart failure and the value of matching RPM with the needs and contextual conditions of each type of patient subgroup.

Second, this work contributes to the digital divide literature, demonstrating that there is more than one way to address the gap in outcomes due to HIT use across patient populations. Specifically, it shows that factors beyond socio-economic status, like social workers and social associations, can help reduce disparities associated with RPM outcomes. At the same time, it highlights that simply increasing resources known to complement RPM will not guarantee successful outcomes, as its important to match the need for RPM with the ability to support RPM related tasks.

Next, I provide an overview of the literature on the importance of patient length of hospital stay, the role RPM can play in the length of patient hospitalizations, and the literature on the digital divide.

3.2. Literature Review

3.2.1. Heart Failure Hospitalizations and the Role of RPM

Heart failure is a progressive disease in which the heart is not able to eject the required amount of blood because of a structural or functional cardiac disorder (Polikandrioti et al. 2015). Heart failure is the leading cause of cardiovascular hospitalization in the US (Shirey et al. 2021), with an average length of hospital stay of 5 days in the US (Rao et al. 2022), and 12 days for patients with frequent emergency department visits (Segar et al. 2022).

A patient's length of hospital stay is influenced by both clinical and non-clinical factors (Almashrafi et al. 2016). When a decision to shorten a patient's length of stay is driven by the need to address high occupancy rates or financial incentives, it can lead to hospital readmissions (Khan et al. 2015; Oh et al. 2018). At the same time, longer patient stays do not guarantee successful patient outcomes (Khan et al. 2015; Sevilla-Cazes et al. 2018; Siddique et al. 2021). In the case of heart failure hospitalizations, research shows that prolonged heart failure length of stay is associated with an increase in the likelihood of hospital-acquired infections and inpatient complications (Khan et al. 2015; Siddique et al. 2021). Furthermore, prolonged hospitalization can lead to negative patient experiences, which can develop into mental distress (Sevilla-Cazes et al. 2018). Overall, research shows that the more time patients spend at the hospital rather than at home, the more likely they will develop depression and anxiety symptoms that will worsen their quality of life (Manemann et al. 2018; Polikandrioti et al. 2015; Saito et al. 2019; Segar et al. 2022) and increase the chance of hospital-acquired infections (Khan et al. 2015; Siddique et al. 2021). Therefore, reducing a patient's length of stay is not only in the best interest of health care organizations seeking to improve their metrics, but also in the best interest of patients seeking to manage their chronic condition more effectively (Segar et al. 2022).

Deciding when to discharge a patient is not an easy decision. After a heart failure event, patients go through a vulnerable phase in which changes in lifestyle can increase the risk for further cardiovascular events (Mesquita et al. 2016). Therefore, health care providers should consider the conditions in which patients live and how the conditions facilitate patient's ability to follow their treatment (White-Williams et al. 2020). Unfortunately, research shows that patients living in areas of socio-economic distress and housing instability will struggle to keep up with the treatment (Rethy et al. 2021; Segar et al. 2022).

Research suggests that as part of hospital-at-home programs, Remote Patient Monitoring (RPM) can help reduce patient's length of stay without significantly increasing patient readmissions (Bao et al. 2020; Ding et al. 2020; Pandor et al. 2013). RPM technologies are pre-programmed mobile devices, such as scales, blood pressure devices, and pulse oximeters, that send vital health data to health care providers (Health 2020). RPM technologies allow caregivers (i.e., nurses and support staff) the ability to receive real-time updates, which can be helpful for chronic care management or post-surgical recovery (Health 2020). Research states that increased communication allows providers to build relationships with patients, specifically those with chronic care conditions (Abdolkhani et al. 2019; Boriani et al. 2017; Vegesna et al. 2017). In the context of chronic heart conditions, research shows that RPM can be cost-effective for vascular and cardiac-related conditions, such as hypertension, as it can help prevent high-cost emergency department visits and prolonged hospitalizations (De Guzman et al. 2022). Furthermore, research shows that when you pair RPM use with a rapid intervention team, it can potentially lower mortality at a faster rate for patients with chronic heart failure (Nakamura et al. 2014).

As in the case of many HITs, the impact of RPM varies across different types of patient populations (Ayer et al. 2019), and the digital divide is often highlighted as a reason why RPM does not consistently work across different types of patient populations (Bricca et al. 2022; Brohman et al. 2019). Therefore, in this research, I examine the literature on the digital divide and, specifically, factors that could contribute to the success of RPM across different contextual conditions.

3.2.2. Digital Divide

Research finds that HIT can help organizations provide consistent service and narrow the differences in outcomes across different patient populations (Srivastava and Shainesh 2015). The use of HIT can help offset hospital quality differences (Jha et al. 2009; Lin et al. 2019), and it can encourage organizational members to follow the process, regardless of any potential social bias (Williams and Wyatt 2015). Research also states that HIT can help connect patients with specialized resources (Abdolkhani et al. 2019), alleviating limitations like physician shortages in areas of deprivation (Gong et al. 2019; Turner et al. 2021; Vong et al. 2017). Unfortunately, the impact of HIT does not always result in expected outcomes, however, and differences in outcomes across patient populations have been found in previous studies (Mastoris et al. 2023). These differences between individuals are what the literature refers to as digital divide (Agarwal et al. 2009; Venkatesh and Sykes 2013).

Research on the digital divide considers gaps in opportunities to access, use, and benefit from technologies between individuals, organizations, and geographic areas (Wei et al. 2011). Research states that technology availability, quality, and affordability are important determinants of IT access and use (Hsieh et al. 2008; Racherla and Mandviwalla 2013). Other determinants include socio-demographic factors, such as age, gender, and ethnicity (Ancker et al. 2017; Hargittai and Hinnant 2008; Vassilakopoulou and Hustad 2021) and socio-economic, such as education, income, and employment status (Agarwal et al. 2009; Lythreatis et al. 2022; Song et al. 2021). Finally, personal attributes, such as trust, motivation, technology perceptions, and social connections can play role in the digital divide (Lythreatis et al. 2022; Mastoris et al. 2023; Song et al. 2021; Zhao et al. 2022).

In health care, we consider digital divide to be the differences in outcomes across patients using health IT not directly attributed to variations in clinical needs (Saeed and Masters 2021). Research states that patients with higher levels of health literacy (Jiang and Cameron 2020) and prior positive experience with technologies (El-Rashidy et al. 2021) will likely benefit from the use of HIT. At the same time, research states that if the patient's health care providers integrate technologies similar to RPM in their workflows, it increases the accessibility, affordability, and communication frequency between them, which increases treatment adherence (Chong et al. 2021; Imran et al. 2021; Lear 2018; Wongvibulsin et al. 2021). Finally, research shows that government initiatives that subsidize patient cost (Hsieh et al. 2011; Lin et al. 2019), or facilitate the adoption of RPM complementarities, such as broadband availability (El-Rashidy et al. 2021; Vegesna et al. 2017), will improve patient's overall experience, which can lead to improved patient outcomes.

Overall, the literature on the digital divide agrees that when technologies do not consider differences between patient's socio-demographic and socio-economic characteristics in their use strategies, they will not help the most disadvantaged groups and could increase the digital divide gap across the population (Díaz Andrade and Techatassanasoontorn 2020; Hsieh et al. 2011; Pethig and Kroenung 2019). Across the literature on the digital divide, we often assume that there is only one ideal way to address the gap in outcomes due to HIT use across patient populations (Lythreatis et al. 2022; Mastoris et al. 2023; Song et al. 2021). Unfortunately, not all patients have the same needs for the technology or have the same access to resources that complement the technologies. Therefore, using RPM combined with complementarities that work on average might not be the best solution across all contexts.

In sum, my literature review shows that a patient's prolonged hospitalization can lead to negative outcomes and the role patients' living conditions can play in reducing their length of stay. RPM can play a role in reducing patient's length of stay and facilitate treatment for patients with heart failure. Unfortunately, the impact of RPM has been inconsistent. Therefore, I argue that given that patients might have different needs for RPM and the resources available to them vary depending on where they live, there is an opportunity to highlight how different set of conditions complement RPM to reduce patient groups average length of hospital stay. At the same time, I find the opportunity to demonstrate that there is more than one way to address the gap in outcomes due to HIT use across patient populations and how simply increasing resources known to complement RPM will not guarantee successful outcomes. Next, I present the research design.

3.3. Research Design

3.3.1. Research Setting

In this study, I construct a longitudinal dataset of patient groups using data from the Healthcare Cost and Utilization Project (HCUP) State Emergency Department Databases (SEDD) for Arizona, Florida, Maryland, and Wisconsin to determine the interactions between patients and health care providers for 2017, 2018, 2019, and 2020. To focus the study on the impact of RPM on heart failure, I only include records from hospitals with either general cardiology services, cardiac rehabilitation, cardiac surgery, or cardiac intensive care. At the same time, I include patient records diagnosed with heart failure-related ICD-10 codes based on the Centers for Medicare and Medicaid Services Circulatory System Heart Failure and Shock Definitions Manual (CMS 2019). The sample selection allows us to ensure I can measure the impact of RPM on heart failure in hospitals that can do so, while, at the same time, excluding visits that are not linked to heart failure.

I complement the dataset with hospital-level data from the American Hospital Association's (AHA) annual survey for 2017 to 2020. I also include county-level variables linked to the patient's home location from County Health Rankings (CHR), the Centers for Disease and Control Prevention Atlas (CDC Atlas), and Area Health Resource Files (AHRF). In contrast with the first study, in this study, I link the county-level variables to the patient's home location instead of the hospital location. I do so to account for patients who do not live in the same area where they seek care for their condition. However, given that RPM programs rarely cross state lines, I exclude patient records who live in different states than the hospitals where they are treated.

While I cannot track patients across years or states, I can group patients of similar characteristics and track the patient group's progress across years. Therefore, I aggregate individual patient records into patient groups based on race, age group, Elixhauser comorbidity index[7]group, admitting hospital, and home location. Each patient group record has a sample weight that I include in the models. I include patient groups from hospitals that either adopted RPM in 2018, 2019 or did not adopt RPM during the entire period of study. After merging the data, I exclude any invalid records or missing data in the variables of interest. For example, I removed any record in which the admission date was after the discharge date.

3.3.2. Variable Selection

Table 3.1 presents an overview of the data sources and operationalization of variables. For the dependent variables, I use the average patient length of stay for patient groups diagnosed with heart failure. Controlling for age and the complexity of the patient's condition, this dependent variable will show us what type of patient characteristics may facilitate the impact of RPM to reduce a patient's length of hospital stay.

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[7] The Elixhauser comorbidity index identifies 38 pre-existing conditions based on ICD-10 diagnosis and builds an index to determine the severity and complexity of a patient's condition (Elixhauser et al. 1998). The comorbidities include: acquired immune deficiency syndrome, alcohol abuse, deficiency anemias, autoimmune conditions, chronic blood loss, leukemia, lymphoma, metastatic cancer, solid tumor without metastasis (in situ), solid tumor without metastasis (malignant), cerebrovascular disease, coagulopathy, dementia, depression, diabetes with chronic complications, diabetes without chronic complications, drug abuse, heart failure, hypertension (complicated), hypertension (uncomplicated), liver disease (mild), liver disease and failure (moderate to severe), chronic pulmonary disease, neurological disorders affecting movement, other neurological disorders, seizures and epilepsy, obesity, paralysis, peripheral vascular disease, psychoses, pulmonary circulation disease, renal kidney failure and disease (moderate), renal kidney failure and disease (severe), hypothyroidism, other thyroid disorders, peptic ulcer with bleeding, valvular disease, and weight loss. Research suggests that the Elixhauser comorbidity index is statistically superior to other indexes to account for acute and chronic conditions (Sharma et al. 2021).

To identify RPM as the variable of interest, I construct an indicator determined by whether the hospital has a local RPM implementation, whether the hospital uses its RPM to manage chronic conditions, and the number of CPT codes used in the hospital linked to RPM installation. For the independent variables for hospital characteristics, I control for the hospital number of beds, admission, emergency department visits, inpatient days, outpatient visits, number of physicians, number of nurses, total personnel, and system memberships from the AHA survey. These variables describe the size and capabilities of each hospital in the sample.

For the independent variables for patient group characteristics, I consider the patient group's race, average charges, average age, and calculate the average Elixhauser comorbidity index.

In terms of patient home location characteristics, I account for the availability of cardiac care resources by including the number of cardiac intensive and cardiac rehabilitation hospitals. Furthermore, I count the total number of workers in the education services, health care, and social assistance industry in the area where the patient lives. This variable is primarily compromised by ambulatory health care services workers, such as registered nurses, personal care aides, and social workers who play a critical role in hospital-at-home programs.

I also account for inpatient and outpatient incremental cost of care for patients with heart disease to control for the cost of services. Finally, I include county characteristics I identified in the literature that are relevant to either the success of managing heart failure or facilitating the use of RPM. They include the percentage of households without broadband availability, median household income, whether the location is an urban metro or rural area, the health status of the area, the level of education through the high school graduation rate, and social associations.

Social association measures the number of membership associations per 10,000 population. Membership associations include, civic organizations, bowling centers, golf clubs, fitness centers, sports organizations, religious organizations, political organizations, labor organizations, business organizations and professional organizations. While this measure is not able to account for family support structures and informal networks, it is still a valid measure to track social support in a community (Kumar et al. 2024). Social support networks have been identified as powerful predictors of health behaviors, suggesting that individuals without a strong social network are less likely to make healthy lifestyle choices than individuals with a strong network (Borges et al. 2021).

Table 3.1. Data Sources and Operationalization of Constructs

Construct	Indicator	Operationalization	Source
Patient RPM outcomes	Average patient length of stay	Average patient length of stay for the patient group with heart failure	HCUP (2017-2020)
RPM Indicator	RPM use	Count of ICD-10 procedure codes linked to RPM installation	HCUP (2017-2020)
	RPM adoption	Hospital local adoption of RPM	AHA (2017-2020)
	RPM for chronic conditions	Hospital use of RPM for chronic conditions	AHA (2017-2020)
Cardiac hospital indicator	Cardiology services	Whether the hospital has cardiology services	AHA (2017-2020)
	Cardiac rehabilitation	Whether the hospital has a cardiac rehabilitation program	AHA (2017-2020)
	Cardiac intensive care	Whether the hospital has cardiac intensive care services	AHA (2017-2020)
Patient Characteristics	Visitlink	Patient identifier that links each patient to all their inpatient and emergency department visits within a year and state	HCUP (2017-2020)
	ICD-10 diagnosis codes	Patient ICD-10 diagnosis codes used to calculate Elixhauser index and identify patient visits linked to heart failure	HCUP (2017-2020)
	Age	Patient age	HCUP (2017-2020)
	Race	Patient Race (1 White, 2 Black, 3 Hispanic, 4 Asian or Pacific Islander)	HCUP (2017-2020)
	Charges	Total charges per visit	HCUP (2017-2020)
	Elixhauser comorbidity index	Elixhauser comorbidity index measures the severity of the patient's medical condition at admission (Elixhauser et al. 1998). To calculate the index, I used 38 predefined comorbidities through a patient's ICD-10 diagnosis codes.	HCUP (2017-2020)
Patient Location Characteristics	FIPS	Patient location FIPS	HCUP (2017-2020)
	Cardiac intensive care hospitals	Number of cardiac intensive care hospitals	CDC Atlas (2017-2020)
	Cardiac rehabilitation hospitals	Number of cardiac rehabilitation hospitals	CDC Atlas (2017-2020)
	Health and social Workforce	Educational services, and health care and social assistance industry workers	AHRF (2017-2020)
	Home health	Number of home health agencies	AHRF (2017-2020)

	Inpatient cost for beneficiaries with heart disease	Inpatient incremental cost of care for Medicare beneficiaries diagnosed with heart disease	CDC Atlas (2017-2020)
	Outpatient cost for beneficiaries with heart disease	Outpatient incremental cost of care for Medicare beneficiaries diagnosed with heart disease	CDC Atlas (2017-2020)
	Limited broadband availability	Households without a broadband internet subscription (%), 2016-2020 (5-year)	CDC Atlas (2017-2020)
	Median income	Median household income	CDC Atlas (2017-2020)
	Urban/Rural status	Urban rural status continuum (1-7)	CDC Atlas (2017-2020)
	Health status	County health status	CHR (2017-2020)
	Highschool graduation rate	High school graduation rate	CHR (2017-2020)
	Social associations	Number of membership associations per 10,000 population.	CHR (2017-2020)
Hospital Characteristics	System membership	Member of a hospital network	AHA (2017-2020)
	Admissions	Total facility admissions	AHA (2017-2020)
	Beds	Total facility beds set up and staffed	AHA (2017-2020)
	ED visits	Emergency department visits	AHA (2017-2020)
	Teaching hospital	Teaching hospital	AHA (2017-2020)
	Total personnel	Full-time total personnel	AHA (2017-2020)

3.3.3. Identification Strategy

In terms of identification strategy, I first establish a baseline for the impact of RPM on the overall population by examining the average treatment effect of RPM on patient group's length of hospital stay. Then, I use causal machine learning to examine the heterogeneous treatment effects of RPM and identify the patient groups that benefit the most from RPM.

I use a difference-in-differences with multiple time periods approach (Callaway and Sant'Anna 2021) to understand the *average treatment effect on the treated* (ATT) of RPM on the average length of stay for different types of patient groups with heart failure. To mitigate concerns of potential endogeneity and self-selection bias, I match the covariate values of the treatment and control groups prior to the availability of RPM using coarsened exact matching (CEM). CEM allows us to prune the dataset and reduce group differences based on hospital and patient group characteristics (Iacus et al. 2012). To add robustness to the analysis, I adopt robust standard errors to correct for potential heteroscedasticity (Wooldridge 2010), and cluster by hospital ID to account for the patient group variables measured at the hospital level. Finally, I examine the group-time average treatment effect in the pretreatment periods to validate the assumption of parallel trends (Callaway and Sant'Anna 2021).

After calculating the average treatment effect of RPM, I conduct a *causal forest subgroup analysis* to identify data-driven patient groups that maximize the impact of RPM using the generalized random forest R package (Wager and Athey 2018). To do so, instead of estimating the treatment effect for the entire population, I create subgroups of patients with similar characteristics by ranking the predicted conditional average treatment effect (CATE) using causal forest.

Similar to the first study, I follow the recommendations from Wang (2022) to structure the panel data to use the causal forest under a first difference approach. The validity of the causal forest relies on the notion of honesty, in which I either use the data points to find the subgroups or use them to estimate the treatment effect within each subgroup (Athey and Wager 2019). At the same time, to ensure the validity of the subgroups and the honesty feature in the causal forest, I must also ensure that I do not fit the model using the data from the observations I use to predict the CATE (Athey and Wager 2019). To do so, I divide the data into K folds, and then cycle through the folds, fitting the CATE on K-1 fold. Using each held-out fold, I separately rank the unseen observations into groups based on their prediction. After merging the rankings, I study the differences in observations in each rank group. Given this is an observational study, I use an Augmented Inverse-Propensity Weighted (AIPW) that is doubly robust and will be consistent with the treatment effect as long as either the propensity score model is correctly specified or the outcome regression is correctly specified (Glynn and Quinn 2010). In the AIPW estimator:

$$\hat{\tau} = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{\mu}_{(1)}(X_i) - \hat{\mu}_{(0)}(X_i) + \frac{W_i}{\hat{e}(X_i)}\left(Y_i - \hat{\mu}_{(1)}(X_i)\right) - \frac{1 - W_i}{1 - \hat{e}(X_i)}\left(Y_i - \hat{\mu}_{(0)}(X_i)\right)\right)$$

The first two terms estimate the conditional expected values for the treated and non-treated groups. Then, the last two terms estimate the propensity scores, which is the probability that the observation will receive the treatment, depending on the confounders. The validity of the estimator relies on the assumptions of overlap and unconfoundeness. I use the previously matched dataset to get similar patient groups in the treatment and control groups to mitigate overlap concerns. Furthermore, I select all covariates that, based on my literature review, can impact the role of HIT on outcomes to mitigate potential concerns with the unconfoundeness assumption. Once I obtain the predicted CATE and rank them based on the strength of the treatment effect, I split the observations into separate groups and compare the heterogeneity of the covariates across subgroups to get a picture of how high treatment effect observations are different than low treatment effect observations across the covariates.

Finally, I leverage *policy learning* to identify data driven recommendations that can guide decision-making to determine who should be treated and who should not (Athey and Wager 2021). Policy learning leverages shallow optimal decision trees that produce transparent and easy-to-interpret rules based on observable characteristics in the data. To provide validity to policy recommendations, it considers the cost of the recommended treatment with respect to the outcome variable (Amram et al. 2022). For example, the monetary cost of providing treatment to each individual (Bonander and Svensson 2021). When the treatment cost is unavailable, Athey and Wager (2021) suggest using the average treatment effect to find the benefit of following the policy recommendations over treating everyone in the group.

Recent research has used policy learning to uncover unexpected heterogeneity in the impact of different health insurance enrollments (Hattab et al. 2024) and health insurance expansions (Kreif et al. 2021). It is important to note that in policy learning, I should ensure that the variables

I use in the models are not gameable or pose legal or ethical concerns (Wager and Athey 2018). For example, a policy learning model shouldn't discriminate based on race. However, while I don't want to use these features for the policy decisions, I do want to keep them in the estimation as they are confounders in the model. Therefore, I will use race in my nuisance components in the generalized random forest but exclude them in the maximization step that produces the policy (Athey and Wager 2021).

Following the recommendations from Athey and Wager (2021) to apply policy learning on observational data, I follow a selection-on-observables strategy under the assumption that by controlling for the specified covariates, I can correct for the different characteristics of each observation used in the sample. The goal is to learn a policy $\pi \epsilon \Pi$ that maps an individual's features $Xi \epsilon \chi$ to a treatment decision $\pi: \chi \rightarrow \{0,1\}$. In this study, the policy assignment is decision to *use RPM* or *seek an alternative*.

I assume we have independent, identically distributed samples (Xi, Yi, Wi) where $Yi \epsilon \mathbb{R}$ is the outcome I want the treatment on, Wi is the observed treatment assignment. First, I estimate the treatment effect of each observation and then assign them to a treatment policy that maximizes the impact of RPM to reduce the average length of stay. I use AIPW with nuisance components estimator from generalized random forests (Chernozhukov et al. 2022)

$$\hat{\pi} = argmax \left\{ \frac{1}{n} \sum_{i=1}^{n} (2\pi(Xi) - 1)(\widehat{\Gamma i} - C) : \pi \epsilon \Pi \right\},$$

$$\hat{\Gamma} i = \hat{\tau}^{(-i)}(Xi) + \frac{Wi - \hat{e}^{(-i)}(Xi)}{\hat{e}^{(-i)}(Xi)\left(1 - \hat{e}^{(-i)}(Xi)\right)} \left(Yi - \hat{f}^{(-i)}(Xi) - \left(Wi - \hat{e}^{(-i)}(Xi) \right) \hat{\tau}^{(-i)}(Xi) \right),$$

Where $\hat{f}$(x) and $\hat{e}(x)$ are a random forest estimate of $\mathbb{E}[Yi|Xi = x]$ and $\mathbb{E}[Wi|Xi = x]$. $\hat{\tau}(\cdot)$ is the causal forest estimate of the conditional average treatment effect, and C is the parameter that measures the cost of the treatment. Similar to Athey and Wager (2021), I set the cost to match the ATE to determine a policy that would highlight observations that maximize the impact of RPM against treating everyone in the group. As a last step, I tune the parameters for all forests by using leave-one-out cross validation, and I run the decision trees to an optimal depth level of 1,2 and 3 to evaluate the consistency of the decision rules and maximize the sum of rewards.

3.4. Empirical Results

Table 3.2 presents the descriptive statistics of the sample after cleaning and matching. As a result, I end with 1,061 patient groups in the treatment group and 6,010 in the control group.

Table 3.2. Descriptive Statistics

Variable	Count	Mean	Std	P25	Median	P75
Patient Characteristics						
Average patient length of stay	28,284	0.5	0.55	0.03	0.3	0.8
Average age	28,284	69.1	14.21	60	71.5	80
Average medical charges	28,284	7,344.2	5,545.79	3,219.91	5,747.6	10,343.9
Average Elixhauser comorbidity index	28,284	3.7	1.39	3	4	5
Cardiac intensive care hospitals	28,284	2.8	3.16	0	2	4
Cardiac rehabilitation hospitals	28,284	3.7	3.37	1	3	5
Health and social workforce	28,284	89,125.7	113,793	11,901	51,844	115,236
Home health	28,284	29.5	50.14	2	7	30
Inpatient cost for beneficiaries with heart disease	28,284	5216	1,076.22	4,461	5,062	5,569
Outpatient cost for beneficiaries with heart disease	28,284	2,341.5	874.53	1,707	2,138	2,691
Limited broadband availability	28,284	14.8	4.88	11.3	13.5	17.6
Median income	28,284	67,711.3	15,589.88	56,000	65,000	72,000
Urban/Rural status	28,284	2.4	1.03	2	2	3
Health status	28,284	0.1	0.03	0.13	0.1	0.2
Highschool graduation rate	28,284	0.8	0.08	0.76	0.8	0.9
Social associations	28,284	9.1	3.36	6.89	8.5	10.9
Hospital Characteristics						
System membership	28,284	0.8	0.4	1	1	1
Admissions	28,284	17,638.4	24,037.33	5,332	12,430	20,330
Beds	28,284	364.2	501.09	106	238	401
ED visits	28,284	70,497.7	101,338	24,117.25	49,633	71,010
Total personnel	28,284	2,006.4	3,097.41	509	1,233.5	2,054

3.4.1. Average Treatment Effects

First, I follow a difference-in-differences approach with multiple periods (Callaway and Sant'Anna 2021) to account for the staggered implementation of RPM across 2018, 2019, and 2020. As the results show in Table 3.3 and Table 3.4, excluding 2020 from the sample, I find that, on average, RPM significantly reduces the average patient's length of stay by -0.061 ($p<0.05$). Looking closely at the implementation waves, I find that the impact is stronger in patient groups from hospitals that adopted RPM in 2018. Unfortunately, when I include 2020 in the sample, the impact of RPM on the average patient length of stay is no longer significant. I further elaborate on the limitations of the 2020 data in the limitation section of the paper.

Table 3.3. ATT of RPM on HF Average Patient Length of Stay

	ATT Excluding COVID	ATT Including COVID
Overall	-0.061 (0.029)*	-0.054 (0.033)
Adoption Waves		
2018 Wave	-0.125 (0.046)*	-0.101 (0.049)
2019 Wave	-0.023 (0.037)	-0.025 (0.043)

Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Robust standard errors clustered by Hospital reported in parentheses.

Table 3.4. Group-Time ATT of RPM on HF Average Patient Length of Stay

Year	ATT 2018 Wave	ATT 2019 Wave
2018	-0.119 (0.044)*	-0.040 (0.051)
2019	-0.131 (0.051)*	-0.023 (0.038)
2020	-0.043 (0.056)	-0.031 (0.048)

Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Robust standard errors clustered by Hospital reported in parentheses.

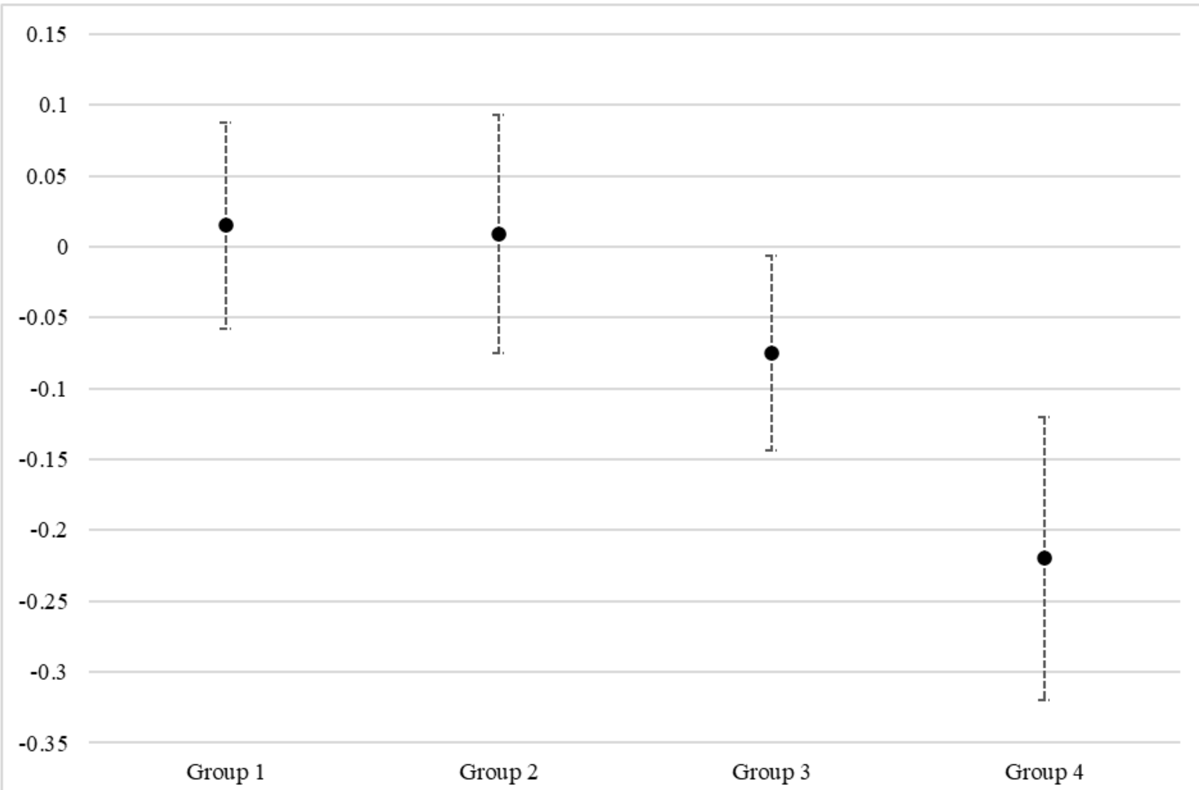
3.4.2. Causal Forest Subgroup Analysis

In terms of data-driven subgroups, I conduct the analysis with and without 2020 in the sample. Similar to the analysis above, introducing 2020 produced inconsistent results with no clear pattern and consistency in the treatment effects, which I further discuss in the limitation section of the paper. Excluding 2020 patient records, I calculate CATEs using the causal forest method, and I rank the observations into 4 subgroups.[8] Table 3.5 shows the AIPW estimators of each group, and as I can observe, the impact of RPM on the average patient's length of stay is significant in group 3 (-0.075, $p<0.05$) and group 4 (-0.220, $p<0.001$). I plot the AIPW estimators in Figure 3.1 for visualization.

[8] We consider different numbers of subgroups and I decided 4 because it offered the least number of groups that can facilitate explainability, while keeping treatment effects statistically significant.

Table 3.5. CATE Estimate by Ranked Group	
Ranking	**Estimate (Std. Error)**
Group 1	0.015 (0.037)
Group 2	0.009 (0.043)
Group 3	-0.075 (0.035)*
Group 4	-0.220 (0.051)***
Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Cluster heteroskedastic robust standard errors reported in parentheses;	

Figure 3.1. Average CATE within Each Ranked Group



Note: Group average CATE estimates with 95% confidence interval bars

In Table 3.6, I visualize the average value of each of the covariates across the groups based on the CATE estimated ranking. In group 3, I can see it has the highest average Elixhauser index (4.1) across all groups, while at the same time, it has the lowest average patient age (59.9). This group lives in areas with the highest median household income ($72,100). Group 3 does not have a strong presence of cardiology and health care resources but does have a high average of social associations (9.36). On the other hand, in group 4, I can observe that the group has the lowest average Elixhauser index (3.42), while at the same time, it has a high average patient age (72.5).

Group 4 has the lowest average median household income at (64,900). Interestingly, this group has a strong presence of cardiology-related resources, such as cardiology intensive hospitals (3.71), and cardiology rehabilitation hospitals (4.57), at a low incremental cardiology outpatient cost ($2,230). This group also has a strong presence in home health agencies (33.4) and the healthcare and social care workforce (110,000).

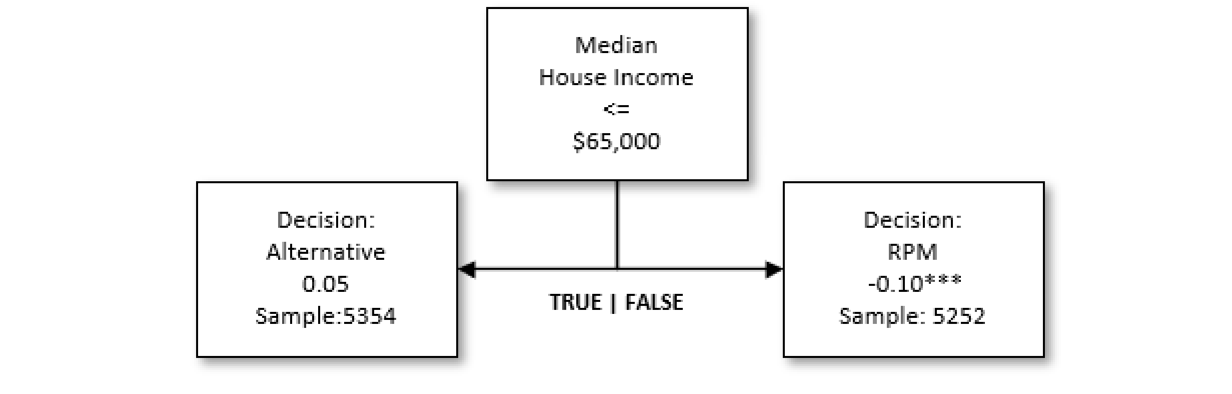
Table 3.6. Average Covariate Values within Each Group

Covariates	Group 1	Group 2	Group 3	Group 4
Average Elixhauser	3.78 (0.025)	3.43 (0.022)	4.11 (0.027)	3.42 (0.021)
Average age	70.9 (0.225)	73.3 (0.204)	59.9 (0.26)	72.5 (0.193)
HS graduation rate	83.9 (0.133)	82.2 (0.138)	85 (0.127)	79.1 (0.013)
Social associations	9.3 (0.061)	8.91 (0.056)	9.36 (0.062)	8.45 (0.044)
Median household income	69800 (308)	66900 (236)	72100 (307)	64900 (209)
Health and social care workforce	77400 (1760)	93800 (1950)	85800 (2100)	110000 (1970)
Home health agencies	26.5 (0.791)	32.3 (0.915)	27.7 (0.791)	33.4 (0.880)
Cardiology inpatient cost	4940 (12.1)	5200 (18.8)	4900 (10.2)	5720 (22.3)
Cardiology outpatient cost	2390 (15.9)	2330 (14.4)	2380 (15.1)	2230 (11.7)
Cardiology intensive hospitals	2.24 (0.049)	2.97 (0.054)	2.44 (0.056)	3.71 (0.054)
Cardiology rehabilitation hospital	3.23 (0.052)	3.92 (0.056)	3.39 (0.063)	4.57 (0.057)
Urban-Rural indicator	2.55 (0.017)	2.36 (0.017)	2.5 (0.017)	2.05 (0.016)
Limited broadband access	14.4 (0.084)	14.4 (0.077)	13.9 (0.083)	15.5 (0.083)

3.4.3. Policy Learning

Next, I use policy trees to illustrate, through the use of transparent decision rules, which groups of patients would maximize the impact of RPM to reduce patient's length of stay. I run the policy trees across three different optimal tree levels and have consistent results across all policy trees. In Figure 3.3, I can observe that an optimal depth 1 policy tree recommends RPM (-0.10, $p<0.001$) for patients living in areas with a median household income greater than $65,000.

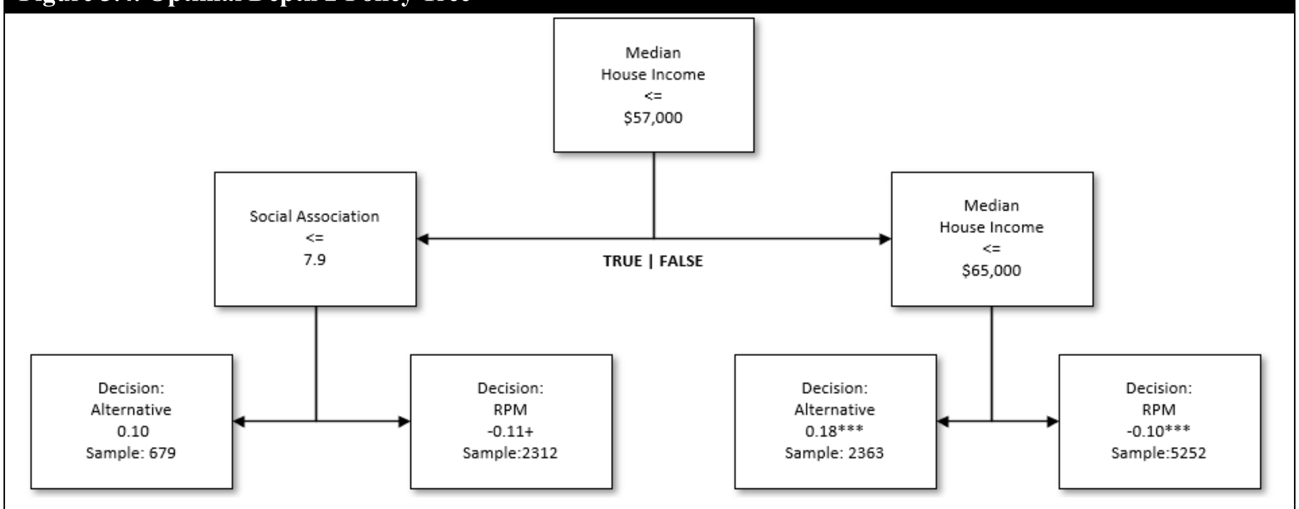
Figure 3.3. Optimal Depth 1 Policy Tree



Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Decision indicates the policy tree recommended actions, AIPW estimate and sample size.

In Figure 3.4, I can observe that an optimal depth 2 policy tree recommends RPM (-0.11, p<0.10) for patients that live in areas where the median household income is less or equal to $57,000 and the social association index is greater than 7.9. Similar to the previous policy tree, it also recommends RPM (-0.10, p<0.001) for patients living in areas with a median household income greater than $65,000. On the other hand, the policy tree suggests seeking an alternative to RPM (0.18, p<0.001) for patients in areas where the median household income is between $57,000 and $ 65,000.

Figure 3.4. Optimal Depth 2 Policy Tree

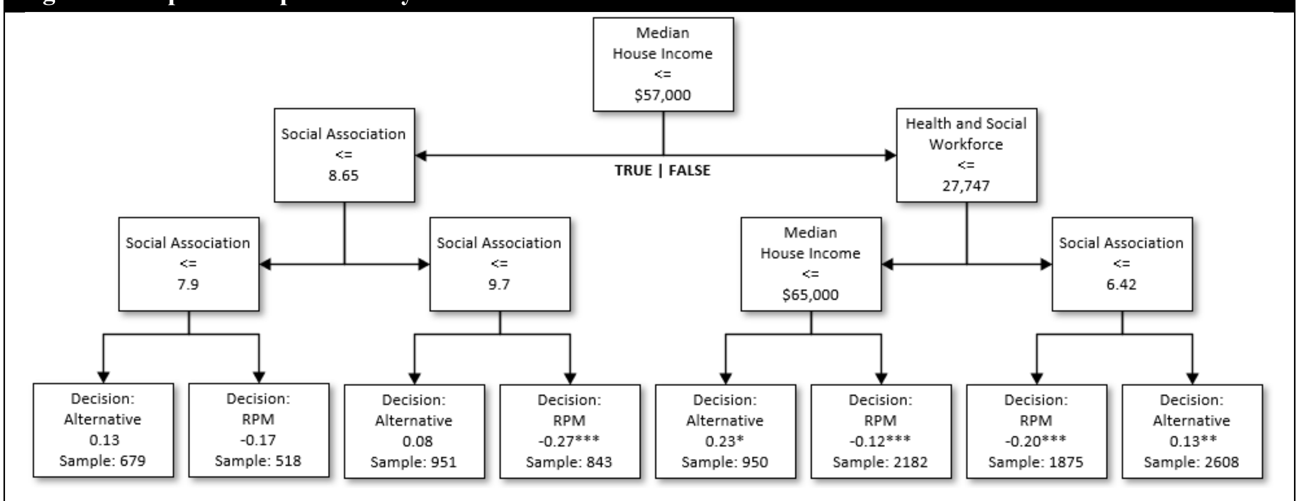


Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Decision indicates the policy tree recommended actions, AIPW estimate and sample size.

In Figure 3.5, I can observe that an optimal depth of 3 policy tree recommends RPM (-0.20, p<0.001) for patients that live in areas where the median household income is greater than $57,000 and the healthcare and social workforce is greater or equal to 27,747 and social association is less than 6.42. Similar to the previous policy tree, it also recommends RPM (-0.27, p<0.001) for patients who live in areas where the median household income is less or equal to $57,000 and the social association index is greater than 9.7. Finally, the policy tree recommends RPM (-0.12, p<0.001) for patients living in areas with a median household income greater than $65,000 and a health care and social workforce less than 27,747.

On the other hand, the policy tree suggests seeking an alternative to RPM (0.13, p<0.01) for patients who live in areas where the median household income is greater than $57,000, the health care and social care workforce is greater than 27,747 and the social association index is greater than 6.42. At the same time, it suggests seeking an alternative to RPM (0.23, p<0.05) for patients that live in areas where the median household income is between $57,000 and $65,000 and the health care and social care workforce is less than 27,747.

Figure 3.5. Optimal Depth 3 Policy Tree



Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Decision indicates the policy tree recommended actions, AIPW estimate and sample size.

3.4.4. Robustness Checks

In terms of robustness checks, I first check that implementing RPM does not lead to unintended negative consequences, such as increasing patient group mortality. As noted in the literature review, a few studies found that early discharge may increase readmission and mortality rates (Khan et al. 2015; Oh et al. 2018). Therefore, I examine the mortality indicator from HCUP as the dependent variable and conduct a difference-in-differences approach with multiple time periods with our matched data (Callaway and Sant'Anna 2021). As the results show in Table 3.7 and Table 3.8, on average, patient groups with RPM had significantly lower mortality rates. These results hold, including 2020 data, and by looking closely at the implementation waves, I find the effect was at its strongest during 2019 for the patient groups from hospitals that adopted RPM in 2019. This robustness test provides validity that discharging patients with RPM does not have unintended negative consequences in those patient groups and, in fact, helps lower mortality.

Table 3.7. ATT of RPM on HF Mortality

	ATT Excluding COVID	ATT Including COVID
Overall	-0.0033 (0.0010)*	-0.0022 (0.0009)*
Adoption Waves		
2018 Wave	-0.0006 (0.0018)	-0.0013 (0.0017)
2019 Wave	-0.0045 (0.0015)*	-0.0026 (0.0012)$^{+}$

Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Robust standard errors clustered by Hospital reported in parentheses.

Table 3.8. Group-Time ATT of RPM on HF Mortality

Year	ATT 2018 Wave	ATT 2019 Wave
2018	0.0008 (0.0021)	-0.0001 (0.0021)
2019	-0.0012 (0.0036)	-0.0039 (0.0013)*
2020	-0.0035 (0.0025)	-0.0013 (0.0021)

Notes: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Robust standard errors clustered by Hospital reported in parentheses.

Next, I evaluate the subgroups from CATE analysis by testing the validity of the causal forest assumptions. To address the overlap assumption, I match the dataset based on the covariates during the pre-treatment period and plot the propensity scores to validate that the scores are not close to one or zero (Figure 3.6). While the propensities are skewed towards the control group, they remain within an acceptable window for the subgroup analysis (Athey et al. 2017). To address the concern that the estimator is biased due to the pre-treatment variables associated with both the treatment and potential outcomes, I measure the sparsity of the product of the propensity score of pre-treatment variables associated with the treatment and the propensity score of pre-treatment variables associated with the outcomes that result in bias (Athey et al. 2017):

$$B = \left(E\left[Y_i^{obs}\middle|W_i = 1\right] - E\left[Y_i^{obs}\middle|W_i = 0\right] - t = \frac{1}{p(1-p)}\right) E[b(X_i)]$$

And with the bias function of: $b(x) = (e(x) - p) * (p(\mu(0, x) - \mu_0) + (1 - p)(\mu(1, x) - \mu_1)$. As a result, the bias is proportional to the covariance of the propensity score and the weighted average of the conditional expectations of the outcomes. The bias function measures the contribution to the overall bias coming from each of the covariates (Athey et al. 2017). I plot the outcomes in Figure 3.7 scaled by the standard deviation of the outcome, and I observe that results do not have a large variance compared to the difference in the average outcomes by treatment effects.

Figure 3.6. Histogram of Estimated Propensity Scores Based on Covariates

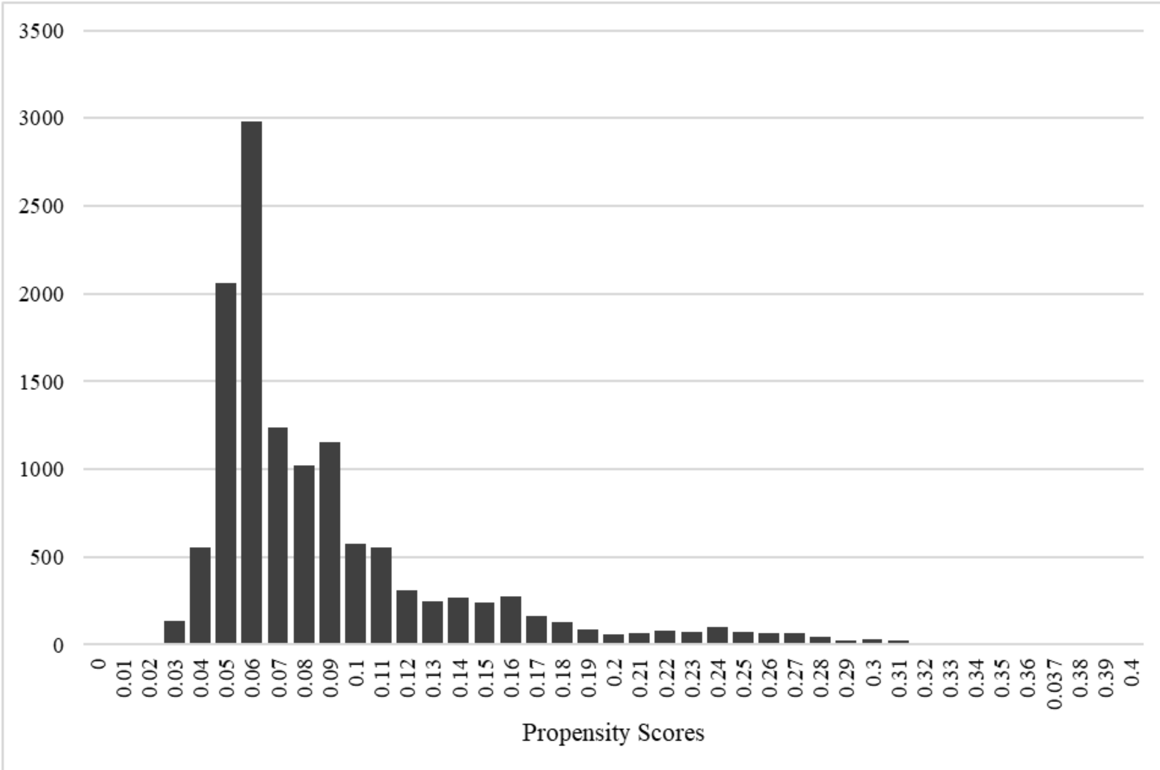
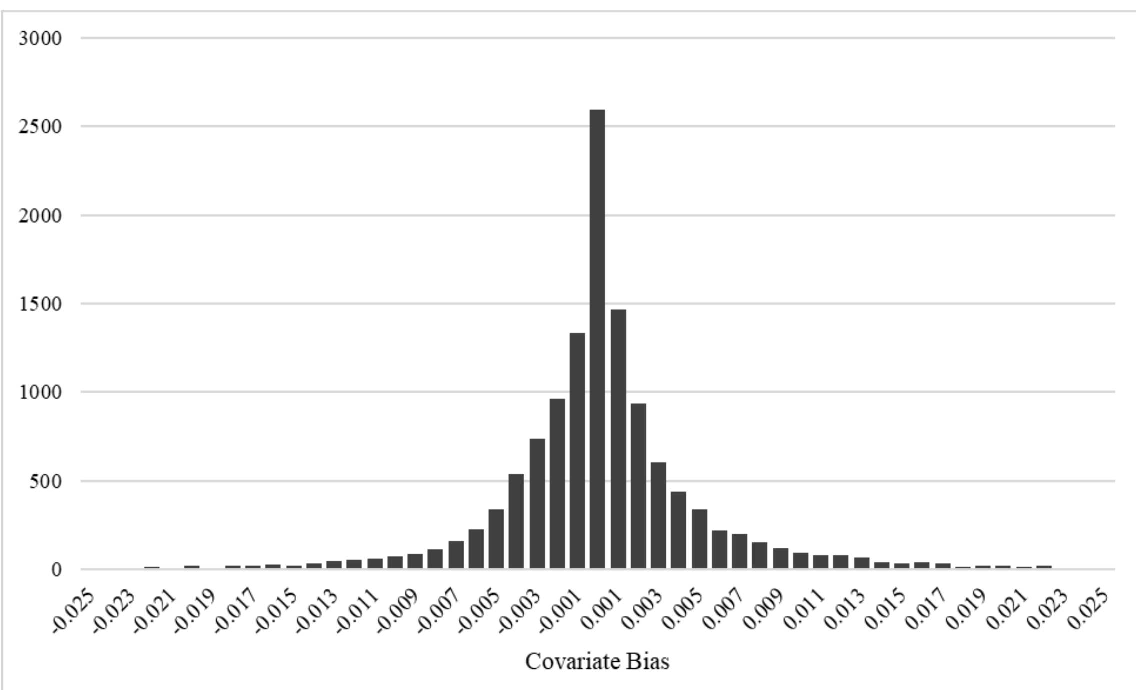


Figure 3.7. Histogram of Covariate Bias



Note: Covariate bias measures the sparsity of the product of the propensity score of pre-treatment variables associated with the treatment and the propensity score of pre-treatment variables associated with the outcomes scaled by the standard deviation

Finally, to assess the validity of the policy learning analysis, I evaluate the treatment effect per leaf node on the hold-out data to check if I have similar average outcomes as the prescribed policy (Athey and Wager 2021; Kitagawa and Tetenov 2018). The results of the policy learning evaluation are presented in Table 3.9.

Table 3.9: Evaluation of Policy Learning

Node	Prescribed Policy Effect	Validation Group Effect	Validation Group Sample Size
		Evaluation of Optimal Depth 1 Policy Tree	
2	0.052 (0.037)	0.105 (0.057)+	1780
3	-0.100 (0.028)***	-0.167 (0.050)***	1756
		Evaluation of Optimal Depth 2 Policy Tree	
4	0.131 (0.100)	-0.052 (0.106)	241
5	-0.105 (0.057)+	0.150 (0.089)+	764
6	0.183 (0.054)***	0.110 (0.090)	775
7	-0.100 (0.028)***	-0.167 (0.050)***	1756
		Evaluation of Optimal Depth 3 Policy Tree	
8	0.131 (0.100)	-0.052 (0.106)	241
9	-0.177 (0.198)	0.547 (0.242)**	186
10	0.081 (0.052)	0.223 (0.128)+	313
11	-0.272 (0.079)***	-0.216 (0.117)+	265
12	0.229 (0.092)*	0.189 (0.194)	321
13	-0.120 (0.031)***	-0.069 (0.038)+	720
14	-0.202 (0.056)***	-0.184 (0.088)*	628
15	0.125 (0.045)**	-0.120 (0.080)	862

Note: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001

In the policy tree with optimal depth of 1, the evaluation results show similar average outcomes as the prescribed policy, which provides validity to the policy tree recommendation that patient groups living in areas with a median household income greater than $65,000 will maximize the impact of RPM on the average length of hospital stay.

In the policy tree with optimal depth of 2, the evaluation results partially support the prescribed policy. Unfortunately, the policy recommendation of RPM for patient groups that live in areas of median household income less than $57,000 and have access to social associations greater than 7.9 was not significant in the held-out sample. The recommendation for RPM to patient groups living in areas with a median household income greater than $65,000 was still significant.

In terms of the policy tree with optimal depth of 3, the evaluation results partially support the prescribed policy, as it validates the recommendation for RPM for three types of patient groups.

The first group consists of patients who live in areas with a median household income greater than \$65,000 and a health care and social workforce of less than 27,747. The second patient group consists of patients living in areas where the median household income is greater than \$57,000, the healthcare and social workforce is greater or equal to 27,747, and social association is less than 6.42. The third patient group consists of patients living in areas with a median household income of less than \$57,000 and access to social associations greater than 9.7. Unfortunately, the recommendations to seek alternatives to RPM were not significant in the evaluation of the policy tree with optimal depth of 3.

3.5. Discussion

In this study, I seek to understand under which combination of conditions RPM reduces the length of hospitalization of patients with health failure. Determining a patient's optimal length of hospital stay goes beyond medical factors, and it's important to consider the conditions in which the patient will continue their rehabilitation and management of their heart failure chronic condition. RPM can reduce the length of patients' hospitalizations by allowing them to be monitored outside of the hospital setting. At the same time, it can reduce the risk associated with prolonged hospitalizations, such as hospital-acquired infections and inpatient complications (Khan et al. 2015; Siddique et al. 2021). This research finds that the impact of RPM varies depending on the patient's characteristics beyond medical factors.

This study finds two distinct types of patient groups that significantly benefit from RPM. In the first group, we can see that RPM can make a difference for patients who are, on average, 60 years old, have high severity of comorbidities, and live in areas with limited health care resources tied to cardiac services. Given the severity of their condition, RPM likely complements the limited availability of health care services, and interestingly, social associations play a key role for those patients. In the second group, we can see that RPM can make a difference for patients who are, on average, 73 years old, have moderate severity of comorbidities, and live in areas with a strong presence of health care and social care resources tied to cardiac services. Given that patients have a higher average age compared to other groups, RPM likely complements hospital-at-home programs and home health services, which may reduce the need for constant hospital visits for populations that tend to be less mobile.

Overall, these findings suggest that RPM can address the needs of two very different types of patient groups, and the characteristics that complement RPM in both scenarios have important contextual differences. For example, assigning RPM to older patient's groups with complex medical severity and limited access to health care and social workers will not reach its intended outcome. As such, health care providers can use these insights to help them determine the optimal length of hospital stay beyond clinical conditions and help them recognize the importance of matching RPM with the needs and contextual conditions of each type of patient groups. In sum, by exploring the heterogeneous impact of RPM, I provide useful and meaningful recommendations that extend current research that only considers the average treatment effect of RPM for patients with heart failure.

3.5.1. Contributions to the Digital Divide

This study makes important contributions to the literature on the digital divide. First, similar to prior research that finds that the most disadvantaged populations are the ones that benefit the least from the adoption of technologies (Brohman et al. 2019), this work finds that the adoption and use of RPM without considering the contextual conditions of the patient groups will likely increase digital divide outcomes. The policy learning findings suggest that patient groups of higher socio-economic status are likely to maximize the impact of RPM. At the same time and in line with prior digital divide literature (Agarwal et al. 2009; Lythreatis et al. 2022; Song et al. 2021), patient groups of lower socio-economic status will struggle to benefit from RPM, especially if they live in isolation and with limited access to health and social care resources. Therefore, assigning RPM to patient groups of lower socio-economic status that lack RPM-supporting conditions will lead to lower RPM performance than other patient groups, increasing the digital divide.

Second, in contrast with prior research simply identifies the conditions that, on average, facilitate or hinder health IT performance across patient populations (El-Rashidy et al. 2021; Saeed and Masters 2021), this study demonstrates that there is more than one way to address the gap in HIT outcomes across the patient population. The findings suggest that health care and, in particular, social care workers can make a difference in complementing RPM by facilitating patient health and technology education for patient groups of lower socio-economic status. At the same time, in the absence of health care and social care resources, a strong presence of social associations can complement RPM by providing social connections that reduce isolation and support RPM-based treatments.

Finally, this study highlights that simply increasing resources known to complement RPM will not guarantee successful outcomes. Although this result did not pass the robustness test, I find that patients groups who live in areas where the median household income is greater than $57,000, with a strong presence of health care and social care workforce and social associations, did not benefit from RPM, and in fact, it increases their average patient length of stay. This is an important warning to recognize that alternatives to RPM might work better in certain conditions. In this case, it could suggest that RPM makes no difference in improving patient outcomes, given the availability of resources. As such, in line with the recommendations of Díaz Andrade and

Techatassanasoontorn (2020), we shouldn't force HIT-driven treatment if the conditions facilitate alternative options.

3.5.2. Limitations

This study has a few limitations. First, while I can determine the hospitals that have RPM and the frequency of their use, I cannot track individual RPM patient outcomes as a result of RPM use. Future studies may consider examining the impact of RPM at a more granular patient level by examining data from hospital systems that cross years and consider outpatient services. Second, while the dataset covers a diverse range of states with different patient populations, I recognize that the findings may not generalize to states with limited access to HIT. Finally, the most salient limitation is the exclusion of COVID-19 from the insights. This study finds that social associations were a significant factor that attenuated potential gaps with the digital divide due to RPM. Due to COVID-19, social gatherings were limited during the early stages of the pandemic, which explains some of the inconsistencies I find when including 2020 in the data. At the same time, the states in the sample had different policies for social gatherings and the health care workforce when operating at maximum capacity. While the study provides valuable insights pre-pandemic, some recommendations may not hold as we move past the post-pandemic. To address this limitation, I envision conducting a follow-up study in which I gather more data beyond the current sample. Then, I will collaborate with a medical billing expert who may provide guidance on ICD10 procedure codes and how they were utilized during COVID for admissions and discharges. Finally, I will look at variables beyond the patient's length of stay and examine the impact on emergency department visits. In the context of heart failure and RPM, more emergency department visits are not necessarily a bad indicator. As research shows, RPM can prompt patients to go to the emergency room at the right time before their condition worsens and leads to more prolonged hospitalizations or death (Khan et al. 2015; Siddique et al. 2021). Despite the limitations, this research, in its current form, provides very valuable contributions to practice and theory.

3.5.3. Research Implications

In terms of practical implications, this work can help health care providers understand how RPM can help different types of patients with heart failure reduce their length of hospital stay. Accounting for the severity of the patient's medical condition, if patients live in an area of lower socio-economic status, providers should consider the availability of social workers who can complement RPM. At the same time, providers should recognize that beyond patients' medical conditions, certain factors may suggest a treatment program without RPM that would match the conditions and resources available to the patients in the area in which they reside. In terms of theoretical implications, this work contributes to the digital divide literature by demonstrating that there is more than one way to address the gap in outcomes due to HIT use across patient populations. At the same time, increasing the resources that, on average, complement RPM does not guarantee successful outcomes; instead, it is how those resources match the needs of each patient group for RPM.

Chapter 4. Dissertation Theoretical Contribution: IS Investment Search

In this dissertation, I identify the conditions under which RPM investments have a beneficial impact on health outcomes.

In the first paper, I examine the heterogeneous impact of RPM on heart failure-related readmissions. Using econometric and machine learning approaches, I find that, on average, RPM adoption reduces heart failure readmissions and that hospitals with more cardiac care specialty resources and a strong background in adopting innovative technologies will benefit the most from the adoption of RPM. At the same time, I find that hospitals in areas of deprivation can leverage their hospital system network to complement RPM. Overall, the results contribute to the literature on health IT for value-based care that extends beyond the hospital setting. The findings have important implications for policymakers deciding how to incentivize and support hospital adoption of RPM.

The second paper examines the heterogeneous impact of RPM on the average length of hospital stay for different types of patient groups with heart failure. Using causal forest subgroup analysis and policy learning, I find a positive impact of RPM across two types of patient groups with different needs and living in areas with different characteristics. Further, I find that patient groups of higher socio-economic status are likely to maximize the impact of RPM, and that social associations and the presence of health care professionals and social workers can complement the use of RPM for patient groups of medium to low socio-economic status. Overall, the paper contributes to the digital divide literature by demonstrating the role of social associations and social workers in the success of RPM for patient groups of low socio-economic status. Furthermore, the findings have important implications for decision-makers to demonstrate how socio-demographic and socio-economic attributes can impact the success of RPM beyond the patient group's medical conditions.

In this section, I reflect on the implications of both studies to propose a contribution to IS investment theories (Atasoy et al. 2018; Mithas et al. 2012; Salge et al. 2015; Sandberg et al. 2014; Turedi and Zhu 2019). In particular, through an inductive consideration of the findings in the two essays, I theorize a novel conditional IS investment search mechanism.

4.1. IS Investment Search

The IS literature has proposed that IS investing is driven by search mechanisms. Specifically, research by Salge et al. (2015) proposes four types of IS investment search mechanisms that guide investment decisions. These mechanisms are triggered by an organization’s need to fix a problem, leverage slack resources, improve process quality, or imitate competitors' IS investment decisions. While these search mechanisms are an excellent basis from which to understand how IS investments are identified and evaluated, my findings suggest that these fundamental IS search mechanisms can be mismatched to the context of the organization (Iyer and Miller 2008; Posen et al. 2018) and often lead to under- or over-investing in IS (Dong et al. 2021). If the current search mechanisms were applied in the context of this research, they would suggest that the search for when and where to invest in RPM and complementarities should be based on the hospital's own historical IS investments or those of a reference organization. However, as described in the first essay, such a search strategy may lead to over-investment of RPM. Specifically, adopting RPM will not have an impact of heart failure readmissions for hospitals that operate in areas with a strong presence of cardiac rehabilitation programs and where the complexity of their patient population's medical condition is not as severe.

Furthermore, I find that these fundamental search mechanisms primarily invite consideration of the interaction of individual resource with the IS investment without examining how the combination of resources would impact the performance of the IS investment. As such, the current search mechanisms may identify IS investments and resources that could address an existing problem. But, they give limited consideration to alternative options if complementary resources are unavailable. For example, in the second study, I find that social associations can complement RPM to reduce average length of hospital stays in the absence of health care resources.

Thus, while the IS search mechanisms offered by Salge et al. (2015) offer an excellent foundation, they do not fully explore the conditions under which organizations can convert IS searches to value appropriation. I therefore draw on my findings to propose a novel IS investment search mechanism that I call *conditional search*. Conditional search is based on Resource Orchestration Theory (ROT) (Sirmon et al. 2010) and configurational theorizing (Furnari et al. 2021), whereby configurations of IS and complementary resources are bundled with respect to contextual conditions. Conditional search is rooted in the search for optimal bundles of IS and structural complements, where optimal is determined by seeking to maximize return on IS investment. I propose that organizations consider not only the technology itself, but also how the technology will fit into the context in which the organization operates, thereby making the consideration of return on investment conditional on the local context.

To introduce this search mechanism, I next discuss the background of IS investment search mechanisms. I subsequently describe the framework for the proposed conditional search mechanism and how the findings provide a basis for it.

4.2. Search Mechanisms for IS Investment Decisions

A search mechanism is a process by which organizations generate alternatives and solutions to existing problems (Argote et al. 2021; Nigam et al. 2016). Work by Salge et al. (2015) proposes four types of search mechanisms to describe what drives IS investment decisions.

The first mechanism proposed by Salge et al. (2015) is *problemistic search,* in which organizations search for IS investments that could help address performance shortfalls (Salge et al. 2015). Under this mechanism, organizations evaluate their aspiration levels with respect to their own historical performance or that of a reference organization (Baum et al. 2005; Pye et al. 2024; Ye et al. 2020). A negative difference between their aspiration level and perceived performance often leads to a problemistic search (Iyer and Miller 2008). Research has shown that problemistic search can be an effective approach to resolve performance differences and facilitate innovation (Karhade and Dong 2021). Unfortunately, research has also found that problemistic search can sometimes be simple-minded and biased (Cyert and March 1963; Desai 2008; Salge et al. 2015). For example, managers' search decisions are at times based on their own experience or within their range of understanding of the industry, which can lead to the misallocation of IS investment (Dhyne et al. 2021). While recent work has suggested ways to improve problemistic search (Posen et al. 2018), concerns remain due to the pressures to deliver results that often lead to mismatch IS investments with the contextual conditions around the organization (Dong et al. 2021; Iyer and Miller 2008; Posen et al. 2018).

The second mechanism proposed is *slack search*, in which organizations use their surplus resources to safely experiment on IS investments with uncertain returns (Salge et al. 2015). Prior research suggests that slack resources increase risk-taking (Bromiley 1991; Iyer and Miller 2008) and the intensity of R&D investments (Chen and Miller 2007). In health care, financial slack has been found to increase the level and persistence of hospitals' largely discretionary R&D activities (Salge 2010; Salge 2012). Prior research has also described how senior leadership in larger hospitals, which arguably possess greater resources, are more inclined to adopt both electronic data processing technologies (Kimberly and Evanisko 1981) and electronic medical records (Angst et al. 2010) than their counterparts in smaller hospitals with fewer slack resources.

The third mechanism is *institutional search*, in which organizations allocate resources to promote the continuous search for improvement beyond short-term goals by identifying existing and future problems and devising ways to address them (Salge et al. 2015). This search tends to be orderly, standardized, and independent of success or failure and is commonly known as institutionalized search (Greve 2003). Institutional search requires sizeable investments in highly task-specific assets such as dedicated facilities, technologies, and employees. Such sunk costs amplify inertial pressures for managers to sustain search activities over time, and to allocate sufficient resources for preserving the asset base (Sutton 1991). Search departments are also expected to craft specific search routines, such as technology sensing (Srinivasan et al. 2002), to make their activities more reliable and amenable to cumulative learning (Chen and Miller 2007). Both slack search and institutional search mechanisms require additional resources dedicated to experimenting with IT investments or working on process improvement projects. Unfortunately, some organizations often lack the resources to make it feasible to follow either a slack or institutional search mechanism (Adler-Milstein et al. 2017). At the same time, research suggests that the impact of slack resources will not always go in the predicted effect direction (Iyer and Miller 2008).

Finally, *mimetic search* is when organizations replicate widely adopted structures and practices within their environment, triggered by their peer investment decisions (Salge et al. 2015). Imitation can help preserve the status quo and reduce the probability of failure (Sirmon and Hitt 2009). Imitation is most salient with regard to those structures and practices that are observable and strategically relevant, but suffer from uncertainty with regard to their performance benefits (DiMaggio and Powell 1983; Greve 1998; Ravichandran et al. 2009). Previous studies in this literature stream reveal that imitation will often be fueled less by an economic rationality than by a normative rationality (Oliver 1997). Unfortunately, this type of investment often results in high performance variation (Ho et al. 2017), in which organizations underinvest or overinvest as a reaction to their environment rather than their capability to appropriate the technology (Ho et al. 2017; Xin and Choudhary 2019).

Existing search mechanisms offer viable solutions for organizations to approach IS investment search processes. However, given the heterogeneity of contextual conditions in which organizations operate, organizations may be unable to maximize their return on all of their IS investments.

4.3. Dissertation Implications on Existing Search Mechanisms

While existing search mechanisms are a good foundation for explaining investment search strategies, recent work suggests an opportunity to improve each mechanism to reduce performance shortfalls (Dong et al. 2021). This research makes a similar argument, but rather than expanding on existing search mechanisms, I draw on insights from the research presented in the two dissertation essays to propose a new mechanism.

First, this research demonstrates the value of examining heterogeneous treatment effects. Unfortunately, existing search mechanisms often attempt to control such heterogeneity, which can lead to under- and over- investment of IS. Current search mechanisms may suggest adopting RPM based on the organization's characteristics. However, the dissertation findings indicate that an RPM investment in areas with strong cardiac rehabilitation programs and low severity of patient population medical condition complexity will lead to no improvement in heart failure readmissions.

Second, I argue that in the attempt of current search mechanisms to find the ideal IS investment and resources that facilitate IS performance, they miss the opportunity to find how different arrangements of resources could reach similar outcomes given the contextual conditions in which they operate. For example, in the first study, I find that organizations will maximize their RPM investment when paired with the presence of cardiac care resources, which is an outcome we would have found with existing search mechanisms. However, current mechanisms would not be able to describe that hospital system memberships can play an important role in complementing RPM in the absence of cardiac care resources.

Finally, I argue that existing search mechanisms often consider the interaction of each individual resource with the IS investment, without examining how combinations of resources would impact the performance of the IS investment. For example, in the second study, I find that RPM will have a greater impact on patient groups of higher socio-economic status, an outcome we would've found with existing search mechanisms. However, instead of giving up on the patient groups of lower socioeconomic status, I find attributes available in their context (i.e., social associations) that allow them to maximize RPM's impact.

Accordingly, based on the findings across both studies, I suggest there is an opportunity to develop a novel conditional search mechanism that embraces heterogeneity and presents how IS investment can work across multiple contextual conditions.

4.4. Conditional Search

The proposal for novel search mechanism is based on the limitations of the existing IS investment search mechanisms and the nature of the findings, which are difficult to explain with current search mechanisms (Table 1). In line with prior research that has considered the impact of complementary resources (Guo et al. 2023; Steelman et al. 2019) and contingency factors (Havakhor et al. 2019) in IS investment performance, this conditional search mechanism is based on Resource Orchestration Theory (Sirmon et al. 2010) and configurational theorizing (Furnari et al. 2021).

Table 3.1: Based on Salge et al. (2015) Search Mechanisms Underpinning IS Investment Decisions

Mechanism	Problemistic Search	Slack Search	Institutionalized Search	Mimetic Search	Conditional Search
Theory	Behavioral Theory of the Firm		Institutional Theory		Resource Orchestration Theory
Trigger	Performance problems	Slack resources	Own investment history	Peer investment decisions	Maximize ROI
Motivation	Identifying solutions to perceived problems in organizational performance	Identifying opportunities to make the best possible use of uncommitted resources	Achieving continuity and predictability in IS resource commitments	Signaling conformity with prevailing IS investment patterns in the organizational reference group	Identify opportunities to optimize the return on IS investments bounded by contextual conditions
Limitations	•Narrow perspective •Overinvestment in IS	•Resource intensive •Inconsistent performance	•Resource intensive •Inconsistent performance	•Inconsistent performance •Overinvestment in IS	•Determining which variable to optimize (e.g., revenue vs. access to care) can be challenging

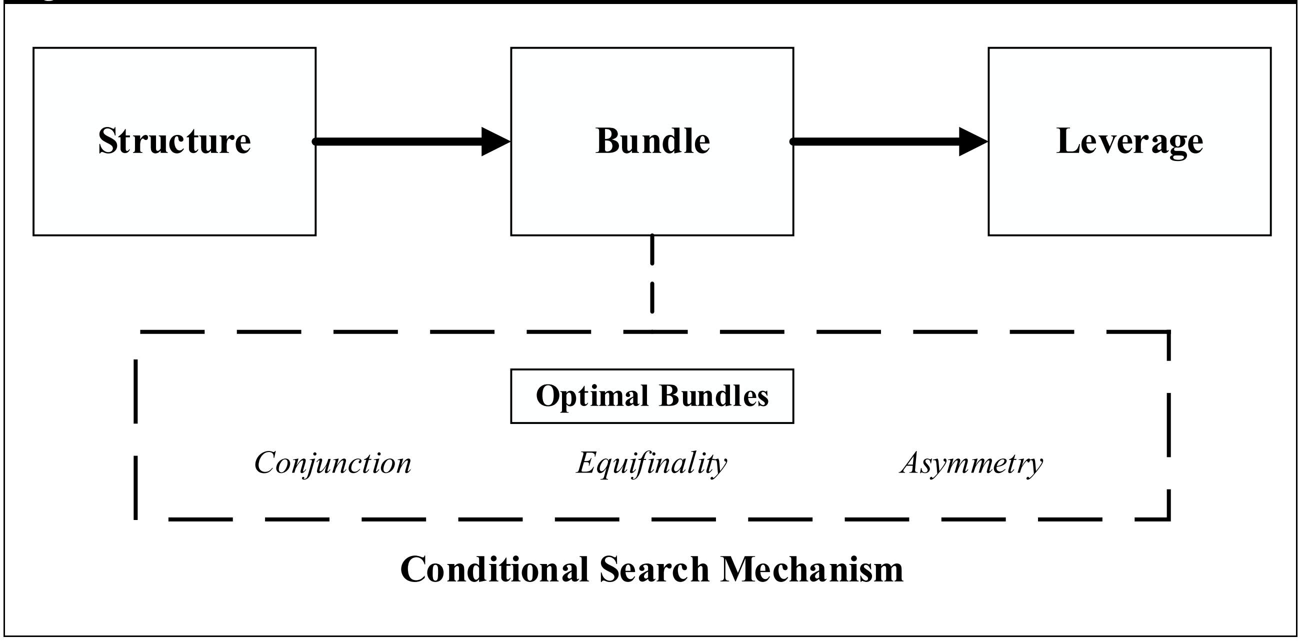
I start by explaining Resource Orchestration Theory (ROT) and then later discuss how configurational theorizing is applied. ROT is an extension of resource-based theory (Barney 1991) that captures how organizations achieve competitive advantages by orchestrating their resources (Sirmon et al. 2010). Prior research has used ROT to examine how organizations, such as startups (Zahra 2021) or family firms (Duran et al. 2016), arrange their resources to improve performance. In health care, we have learned how different individuals require different resources during a crisis

(Pan et al. 2020), how different municipalities can arrange their resources uniquely to address their specific needs (Kauppi and Taponen 2022), and how organizations orchestrate their resources to create resilient humanitarian operations in sync with the environmental context to reach population-level goals (Baltas et al. 2022).

Regarding investment decisions, ROT states that organizations attempting to replicate the investment strategies of industry leaders and competitors will likely produce average returns and not maximize their return on investment (Sirmon and Hitt 2009). ROT suggests that optimal investment decisions are determined by the fit between resource investments and the means of deployment that consider contextual conditions, and that any deviation or misfit will negatively affect performance (Arrfelt et al. 2015; Sirmon et al. 2010; Sirmon and Hitt 2009). This is particularly important compared to other investment search strategies, as the notion of fit can reduce both under- and over-investing of resources (Arrfelt et al. 2015). However, simply maximizing resources believed to complement specific investments does not guarantee successful outcomes and, in fact, often results in investment inefficiencies. For example, Sirmon and Hitt (2009) find that maximizing investments in human capital to complement standard service offerings can result in investment inefficiencies. Thus, what is needed is an examination of how IS investment and complementary resources can be configured in relation to local, contextual conditions.

As illustrated in Figure 1, ROT follows such a process in which an organization *structures* their resource portfolio, *bundles* their resources to build capabilities, and *leverages* those capabilities to create value (Hitt et al. 2016; Li et al. 2023; Sirmon et al. 2010; Yu et al. 2022). The conditional search mechanism focuses on the bundle stage.

Figure 3.1: Conditional Search Mechanism



To identify optimal bundles, the conditional search mechanism follows a configurational theorizing perspective (Furnari et al. 2021) that describes how different arrangements of conditions might fit better than others in different types of contexts and, as a result, provide predictions that can help organizations and populations understand which set of characteristics and decisions work best given their particular circumstances (Furnari et al. 2021). In contrast with prior research that leverages configurational theorizing through QCA and Fuzzy-set QCA (Hu et al. 2023; Park and Mithas 2020; Raab et al. 2013), I theorize the configurations inductively through the use of causal machine learning (Athey and Imbens 2019), answering the call of Furnari et al. (2021) to incorporate machine learning methods to theorize data-driven configurations.

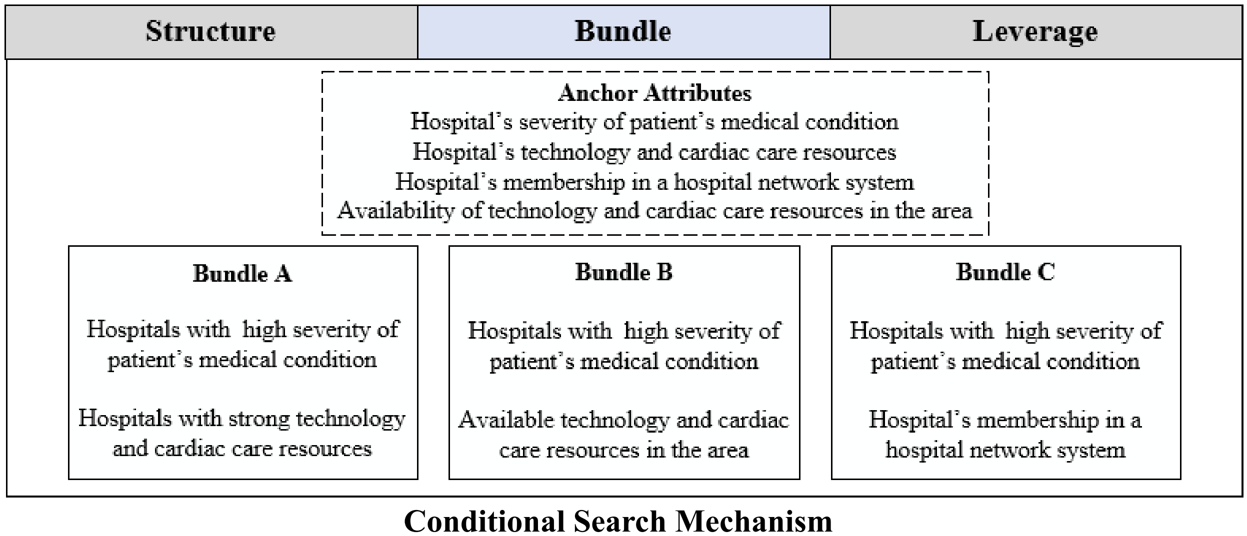
A configurational perspective emphasizes three characteristics: conjunction, equifinality, and asymmetrical relationships (Furnari et al. 2021). *Conjunction* focuses on how or why exploratory attributes combined result in a given outcome, and *equifinality* explains how different combinations of attributes can reach a similar final stage. In contrast with a unifinal perspective, which treats alternative explanatory variables as controls to parcel out confounding effects, a configurational perspective considers how one or more explanatory factors can serve as substitutes for one another, creating a functional equivalence (Meyer et al. 1993). Finally, *asymmetrical relationships* between attributes describe how the absence or presence of factors is not symmetrically linked with the outcome variables. Therefore, under a configurational perspective, "the more of X, the more of Y" does not imply that "the less of X, the less of Y". Finally, the conditional search mechanism relies on causal machine learning (Wager and Athey 2018) to identify heterogeneity patterns and build data driven bundles that organizations can leverage to find conditions ideal for maximizing IS performance.

Taken together, the proposed conditional search mechanism can address shortcomings of other mechanisms that often result in under- or over-investment and allow organizations to maximize their return on IS investments bounded by their contextual conditions. In particular, the search mechanism considers the possibility that multiple configurations can reach similar outcomes, and it explains attributes that lead to those configurations.

4.5. Application of the IS Investment Conditional Search Mechanism

Next, I demonstrate the application of the conditional search mechanism across the two dissertation studies. Figure 2 provides an overview of the conditional search mechanism applied to the first study, in which I seek to understand what types of hospitals and regions the adoption of RPM most reduces chronic heart conditions related readmissions.

Figure 3.2: Search for RPM Investments to Reduce Chronic Heart Conditions Readmissions

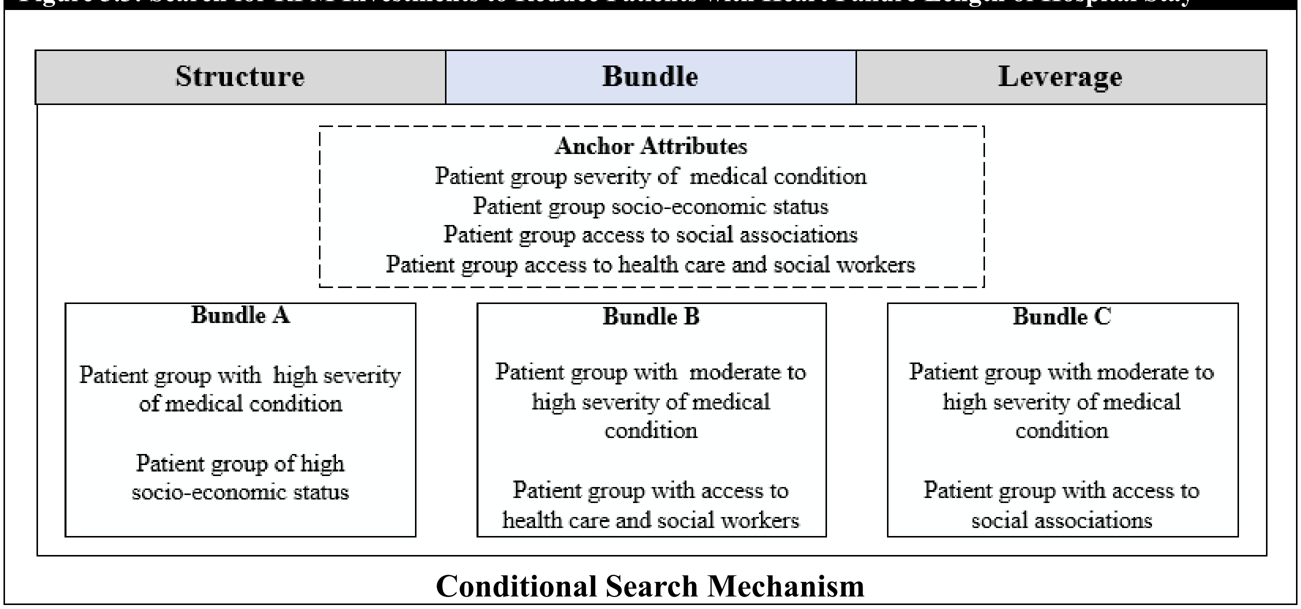


To begin, the search mechanism identifies anchor attributes that drive data-driven search decisions and describes how, combined with each other, they can explain the outcome of interest. In this context, I identify four anchor attributes: hospital's severity of patient's medical condition, hospital's technology and cardiac care resources, hospital's membership in a hospital network system, and the availability of cardiac care and technology resources in the area in which the hospital operates.

Based on the anchor attributes, I link them to form bundles using configurational theorizing properties focused conjunction, equifinality, and asymmetrical relationships. First, I consider the interdependence links among the attributes. If hospitals don't have a patient population with complex medical conditions, then investing in RPM and complementary resources may not be the optimal investment choice. Next, I consider how multiple configurations may be equally effective in explaining the outcome and how the absence of attributes connects with the presence of different attributes to form comparable bundles. I find that hospitals with strong technology and cardiac care resources are likely to maximize their investment in RPM to meet the high severity of their patient population's medical condition. In the absence of strong cardiac care resources, hospitals could leverage the availability of cardiac care resources in the area in which they operate to complement their RPM-related task and reach similar outcomes. At the same time, in the absence of cardiac care resources to interpret RPM data, hospitals could leverage their membership in a hospital network system to interpret RPM data to maximize their RPM investment. As a result of the conditional search mechanism, I find three types of bundles that hospitals can leverage to maximize their investment in RPM to reduce their heart failure-related readmissions.

Figure 3 provides an overview of the conditional search mechanism applied to the second study, in which I seek to understand the impact of RPM investment in reducing patient length of hospital stay across different types of patient groups with heart failure.

Figure 3.3: Search for RPM Investments to Reduce Patients with Heart Failure Length of Hospital Stay



To begin, the search mechanism identifies key attributes that drive data-driven search decisions, and describe, how combined with each other, can explain the outcome of interest. In this context, I identify four anchor attributes: patient group severity of medical condition, patient group socio-economic status, patient group access to health care, home health and social workers, and patient group access to social associations.

Based on the anchor attributes, I link them to form bundles using configurational theorizing properties, in which I again focus on conjunction, equifinality, and asymmetrical relationships. First, I consider the interdependent links among the attributes. If patient groups don't have at least a moderate to severe complexity of heart failure, then investing in RPM and complementary resources may not be the optimal investment choice. Next, I consider how multiple configurations may be equally effective in explaining the outcome and how the absence of attributes connects with the presence of different attributes to form comparable bundles. I find that patients who live in areas of high socio-economic status are likely to maximize the impact of RPM to meet the high severity of their heart failure condition. In the absence of patient groups living in areas of high socio-economic status, patient groups can leverage health care, home health, and social workers to complement RPM investments to help with patient education and treatment adherence. Finally, if patient groups live in areas of lower socio-economic status and have limited health care, home health, and social workers, social association availability can complement RPM's impact. As a result of the conditional search mechanism, I find three different types of bundles of patient groups that can leverage their investment of RPM to reduce the patient's average length of hospital stay.

4.6. Conclusion

In conclusion, in this dissertation I argue that RPM can play a critical role in facilitating health care services and improving health outcomes for patients with heart failure. Given the complexity of this chronic disease and the diversity of hospital and patient characteristics, I advocate the importance of examining heterogeneous treatment effects. Using econometric and causal machine learning, I find that no single health care configuration is ideal for facilitating the adoption and use of RPM, but rather that different types of configurations can provide similar hospital and patient outcomes. As such, this dissertation has important implications for policymakers deciding how to incentivize and support hospital adoption of RPM and for health care providers in their efforts to design effective strategies for adoption and use of RPM for patients with heart failure. Finally, using the insights from the two dissertation studies, I contribute to IS investment search theories by proposing a new search mechanism that can help organizations maximize the return on IS investment.

4.7. References

Abdolkhani, R., Gray, K., Borda, A., and DeSouza, R. 2019. "Patient-Generated Health Data Management and Quality Challenges in Remote Patient Monitoring," *JAMIA Open* (2:4), pp. 471-478.

Adams, D., Wolfe, A. J., Warren, J., Laberge, A., Richards, A. C., Herzer, K., and Fleisher, L. A. 2023. "Initial Findings from an Acute Hospital Care at Home Waiver Initiative," *JAMA Health Forum* (4:11), p. e233667.

Adjerid, I., Acquisti, A., Telang, R., Padman, R., and Adler-Milstein, J. 2016. "The Impact of Privacy Regulation and Technology Incentives: The Case of Health Information Exchanges," *Management Science* (62:4), pp. 1042-1063.

Adler-Milstein, J., Holmgren, A. J., Kralovec, P., Worzala, C., Searcy, T., and Patel, V. 2017. "Electronic Health Record Adoption in Us Hospitals: The Emergence of a Digital "Advanced Use" Divide," *Journal of the American Medical Informatics Association* (24:6), pp. 1142-1148.

Adler-Milstein, J., and Jha, A. K. 2017. "Hitech Act Drove Large Gains in Hospital Electronic Health Record Adoption," *Health Affairs* (36:8), pp. 1416-1422.

Agarwal, R., Animesh, A., and Prasad, K. 2009. "Social Interactions and the “Digital Divide”: Explaining Variations in Internet Use," *Information Systems Research* (20:2), pp. 277-294.

Agarwal, R., Gao, G., DesRoches, C., and Jha, A. K. 2010. "Research Commentary—the Digital Transformation of Healthcare: Current Status and the Road Ahead," *Information Systems Research* (21:4), pp. 796-809.

Ahmad, K., Chen, E. W., Nazir, U., Cotts, W., Andrade, A., Trivedi, A. N., Erqou, S., and Wu, W. C. 2019. "Regional Variation in the Association of Poverty and Heart Failure Mortality in the 3135 Counties of the United States," *Journal of the American Heart Association* (8:18), p. e012422.

Almashrafi, A., Elmontsri, M., and Aylin, P. 2016. "Systematic Review of Factors Influencing Length of Stay in Icu after Adult Cardiac Surgery," *BMC Health Serv Res* (16), p. 318.

Amram, M., Dunn, J., and Zhuo, Y. D. 2022. "Optimal Policy Trees," *Machine Learning* (111:7), pp. 2741-2768.

Ancker, J. S., Nosal, S., Hauser, D., Way, C., and Calman, N. 2017. "Access Policy and the Digital Divide in Patient Access to Medical Records," *Health Policy and Technology* (6:1), pp. 3-11.

Angst, C., Block, E. S., D’Arcy, J., and Kelley, K. 2017. "When Do IT Security Investments Matter? Accounting for the Influence of Institutional Factors in the Context of Healthcare Data Breaches," *MIS Quarterly* (41:3), pp. 893-A898.

Angst, C. M., Agarwal, R., Sambamurthy, V., and Kelley, K. 2010. "Social Contagion and Information Technology Diffusion: The Adoption of Electronic Medical Records in Us Hospitals," *Management Science* (56:8), pp. 1219-1241.

Argote, L., Lee, S., and Park, J. 2021. "Organizational Learning Processes and Outcomes: Major Findings and Future Research Directions," *Management Science* (67:9), pp. 5399-5429.

Arrfelt, M., Wiseman, R. M., McNamara, G., and Hult, G. T. M. 2015. "Examining a Key Corporate Role: The Influence of Capital Allocation Competency on Business Unit Performance," *Strategic Management Journal* (36:7), pp. 1017-1034.

Asagbra, O. E., Burke, D., and Liang, H. 2019. "The Association between Patient Engagement HIT Functionalities and Quality of Care: Does More Mean Better?," *International Journal of Medical Informatics* (130), p. 103893.

Atasoy, H., Chen, P.-y., and Ganju, K. 2018. "The Spillover Effects of Health IT Investments on Regional Healthcare Costs," *Management Science* (64:6), pp. 2515-2534.

Athey, S., Imbens, G., Pham, T., and Wager, S. 2017. " Estimating Average Treatment Effects: Supplementary Analyses and Remaining Challenges," *American Economic Review* (5:107), pp. 278-281.

Athey, S., and Imbens, G. W. 2019. "Machine Learning Methods That Economists Should Know About," *Annual Review of Economics* (11), pp. 685-725.

Athey, S., and Wager, S. 2019. "Estimating Treatment Effects with Causal Forests: An Application," *Observational Studies* (5:2), pp. 37-51.

Athey, S., and Wager, S. 2021. "Policy Learning with Observational Data," *Econometrica* (89:1), pp. 133-161.

Auener, S. L., Remers, T. E. P., van Dulmen, S. A., Westert, G. P., Kool, R. B., and Jeurissen, P. P. T. 2021. "The Effect of Noninvasive Telemonitoring for Chronic Heart Failure on Health Care Utilization: Systematic Review," *Journal of Medical Internet Research* (23:9), p. e26744.

Ayabakan, S., Bardhan, I. R., and Zheng, Z. 2023. "Impact of Telehealth and Process Virtualization on Healthcare Utilization," *Information Systems Research* (35:1), pp. 45-65.

Ayer, T., Ayvaci, M. U. S., Karaca, Z., and Vlachy, J. 2019. "The Impact of Health Information Exchanges on Emergency Department Length of Stay," *Production and Operations Management* (28:3), pp. 740-758.

Baird, A., Cheng, Y., and Xia, Y. 2022. "Telehealth Adoption and Discontinuation by Us Hospitals: Results from 2 Quasi-Natural Experiments," *JMIR formative research* (6:2), p. e28979.

Baltas, K., Jayasekera, R., Uddin, G. S., and Papadopoulos, T. 2022. "The Role of Resource Orchestration in Humanitarian Operations: A Covid-19 Case in the Us Healthcare," *Annals of Operations Research*), pp. 1-30.

Bao, C., Bardhan, I. R., Singh, H., Meyer, B. A., and Kirksey, K. 2020. "Patient–Provider Engagement and Its Impact on Health Outcomes: A Longitudinal Study of Patient Portal Use," *MIS Quarterly* (44:2), pp. 699-723.

Bardhan, I., Oh, J.-h., Zheng, Z., and Kirksey, K. 2015. "Predictive Analytics for Readmission of Patients with Congestive Heart Failure," *Information Systems Research* (26:1), pp. 19-39.

Barney, J. 1991. "Firm Resources and Sustained Competitive Advantage," *Journal of Management* (17:1), pp. 99-120.

Baum, J. A., Rowley, T. J., Shipilov, A. V., and Chuang, Y.-T. 2005. "Dancing with Strangers: Aspiration Performance and the Search for Underwriting Syndicate Partners," *Administrative science quarterly* (50:4), pp. 536-575.

Bavafa, H., Hitt, L. M., and Terwiesch, C. 2018. "The Impact of E-Visits on Visit Frequencies and Patient Health: Evidence from Primary Care," *Management Science* (64:12), pp. 5461-5480.

Benjamin, E. J., Virani, S. S., Callaway, C. W., Chamberlain, A. M., Chang, A. R., Cheng, S., Chiuve, S. E., Cushman, M., Delling, F. N., and Deo, R. 2018. "Heart Disease and Stroke Statistics—2018 Update: A Report from the American Heart Association," *Circulation* (137:12), pp. e67-e492.

Berry Jaeker, J. A., and Tucker, A. L. 2017. "Past the Point of Speeding Up: The Negative Effects of Workload Saturation on Efficiency and Patient Severity," *Management Science* (63:4), pp. 1042-1062.

Bhargava, H. K., and Mishra, A. N. 2014. "Electronic Medical Records and Physician Productivity: Evidence from Panel Data Analysis," *Management Science* (60:10), pp. 2543-2562.

Bhatia, A., and Maddox, T. M. 2021. "Remote Patient Monitoring in Heart Failure: Factors for Clinical Efficacy," *International Journal of Heart Failure* (3:1), pp. 31-50.

Bilazarian, A. 2022. "Primary Care Practice Structural Capabilities in Health Professional Shortage Areas," *American Journal of Managed Care* (28:5).

Bonander, C., and Svensson, M. 2021. "Using Causal Forests to Assess Heterogeneity in Cost-Effectiveness Analysis," *Health Economics* (30:8), pp. 1818-1832.

Borges, C. M., Pollock, J. C., Crowley, M., Purandare, R., Sparano, J., and Spike, K. 2021. "Social Capital or Vulnerability: Which Has the Stronger Connection with Selected U.S. Health Outcomes?," *SSM - Population Health* (15), p. 100812.

Boriani, G., Da Costa, A., Quesada, A., Ricci, R. P., Favale, S., Boscolo, G., Clementy, N., Amori, V., Mangoni di S. Stefano, L., and Burri, H. 2017. "Effects of Remote Monitoring on Clinical Outcomes and Use of Healthcare Resources in Heart Failure Patients with Biventricular Defibrillators: Results of the More-Care Multicentre Randomized Controlled Trial," *European Journal of Heart Failure* (19:3), pp. 416-425.

Brahmbhatt, D. H., Ross, H. J., and Moayedi, Y. 2022. "Digital Technology Application for Improved Responses to Health Care Challenges: Lessons Learned from Covid-19," *Canadian Journal of Cardiology* (38:2), pp. 279-291.

Bricca, A., Pellegrini, A., Zangger, G., Ahler, J., Jäger, M., and Skou, S. T. 2022. "The Quality of Health Apps and Their Potential to Promote Behavior Change in Patients with a Chronic Condition or Multimorbidity: Systematic Search in App Store and Google Play," *JMIR Mhealth Uhealth* (10:2), p. e33168.

Brohman, K., Addas, S., Dixon, J., and Pinsonneault, A. 2019. "Cascading Feedback: A Longitudinal Study of a Feedback Ecosystem for Telemonitoring Patients with Chronic Disease," *MIS Quarterly* (43:4).

Bromiley, P. 1991. "Testing a Causal Model of Corporate Risk Taking and Performance," *Academy of Management Journal* (34:1), pp. 37-59.

Bronsoler, A., Doyle, J., and Van Reenen, J. 2022. "The Impact of Health Information and Communication Technology on Clinical Quality, Productivity, and Workers," *Annual Review of Economics* (14:1), pp. 23-46.

Brown, T. M., Parmar, G., Durant, R. W., Halanych, J. H., Hovater, M. M., Muntner, P., Prineas, R. J., Roth, D. L., Samdarshi, T. E., and Safford, M. M. 2011. "Health Professional Shortage Areas, Insurance Status, and Cardiovascular Disease Prevention in the Reasons for Geographic and Racial Differences in Stroke (Regards) Study," *Journal of Health Care for the Poor and Underserved* (22:4), p. 1179.

Butts, K., and Gardner, J. 2021. "{Did2s}: Two-Stage Difference-in-Differences," *arXiv preprint arXiv:2109.05913*).

Callaway, B., and Sant'Anna, P. H. 2021. "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics* (225:2), pp. 200-230.

CDC, C. f. D. C. a. P. 2022. "Heart Disease in the United States." Retrieved 4/10/23, 2023, from https://www.cdc.gov/nchs/hus/topics/heart-disease-deaths.htm

Chandrasekaran, R., Sharma, P., and Moustakas, E. 2023. "Exploring Disparities in Healthcare Wearable Use among Cardiovascular Patients: Findings from a National Survey," *Reviews in Cardiovascular Medicine* (24:11), p. 307.

Chang, Y. B., and Gurbaxani, V. 2013. "An Empirical Analysis of Technical Efficiency: The Role of IT Intensity and Competition," *Information Systems Research* (24:3), pp. 561-578.

Chen, M., Guo, S., and Tan, X. 2019. "Does Health Information Exchange Improve Patient Outcomes? Empirical Evidence from Florida Hospitals," *Health Affairs* (38:2), pp. 197-204.

Chen, W. R., and Miller, K. D. 2007. "Situational and Institutional Determinants of Firms' R&D Search Intensity," *Strategic Management Journal* (28:4), pp. 369-381.

Cheng, N., Li, H., and Bang, Y. 2023. "Pay-for-Performance Schemes and Hospital HIT Adoption," *Decision Support Systems* (164).

Chernozhukov, V., Demirer, M., Duflo, E., and Fernandez-Val, I. 2018. "Generic Machine Learning Inference on Heterogeneous Treatment Effects in Randomized Experiments, with an Application to Immunization in India." National Bureau of Economic Research.

Chernozhukov, V., Escanciano, J. C., Ichimura, H., Newey, W. K., and Robins, J. M. 2022. "Locally Robust Semiparametric Estimation," *Econometrica* (90:4), pp. 1501-1535.

Chong, M. S., Sit, J. W. H., Karthikesu, K., and Chair, S. Y. 2021. "Effectiveness of Technology-Assisted Cardiac Rehabilitation: A Systematic Review and Meta-Analysis," *International Journal of Nursing Studies* (124), p. 104087.

Chou, Y. C., Chuang, H. H. C., Chou, P., and Oliva, R. 2023. "Supervised Machine Learning for Theory Building and Testing: Opportunities in Operations Management," *Journal of Operations Management* (69:4), pp. 643-675.

Cinelli, C., and Hazlett, C. 2020. "Making Sense of Sensitivity: Extending Omitted Variable Bias," *Journal of the Royal Statistical Society Series B: Statistical Methodology* (82:1), pp. 39-67.

CMS, C. f. M. a. M. S. 2012. "Hospital Readmissions Reduction Program (HRRP)." Retrieved 11/06/2021, 2024, from https://www.cms.gov/medicare/quality/value-based-programs/hospital-readmissions

CMS, C. f. M. a. M. S. 2019. "Icd-10-Cm/Pcs Ms-Drg V37.0 Definitions Manual." 2024, from https://www.cms.gov/icd10m/version37-fullcode-cms/fullcode_cms/P0140.html

Colicchio, T. K., Borbolla, D., Colicchio, V. D., Scammon, D. L., Del Fiol, G., Facelli, J. C., Bowes, W. A., 3rd, and Narus, S. P. 2019. "Looking Behind the Curtain: Identifying Factors Contributing to Changes on Care Outcomes During a Large Commercial EHR Implementation," *EGEMS (Wash DC)* (7:1), p. 21.

Cyert, R. M., and March, J. G. 1963. *A Behavioral Theory of the Firm*. Upper Saddle River, NJ, US: Prentice Hall/Pearson Education.

Dandl, S., Haslinger, C., Hothorn, T., Seibold, H., Sverdrup, E., Wager, S., and Zeileis, A. 2024. "What Makes Forest-Based Heterogeneous Treatment Effect Estimators Work?," *The Annals of Applied Statistics* (18:1), pp. 506-528.

Daniel, O. U. 2018. "Effects of Health Information Technology and Health Information Exchanges on Readmissions and Length of Stay," *Health Policy and Technology* (7:3), pp. 281-286.

De Guzman, K. R., Snoswell, C. L., Taylor, M. L., Gray, L. C., and Caffery, L. J. 2022. "Economic Evaluations of Remote Patient Monitoring for Chronic Disease: A Systematic Review," *Value Health* (25:6), pp. 897-913.

Desai, V. M. 2008. "Constrained Growth: How Experience, Legitimacy, and Age Influence Risk Taking in Organizations," *Organization Science* (19:4), pp. 594-608.

Dhyne, E., Konings, J., Van den bosch, J., and Vanormelingen, S. 2021. "The Return on Information Technology: Who Benefits Most?," *Information Systems Research* (32:1), pp. 194-211.

Díaz Andrade, A., and Techatassanasoontorn, A. A. 2020. "Digital Enforcement: Rethinking the Pursuit of a Digitally-Enabled Society," *Information Systems Journal* (31:1), pp. 184-197.

DiMaggio, P. J., and Powell, W. W. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields," *American Sociological Review* (48:2), pp. 147-160.

Ding, H., Chen, S. H., Edwards, I., Jayasena, R., Doecke, J., Layland, J., Yang, I. A., and Maiorana, A. 2020. "Effects of Different Telemonitoring Strategies on Chronic Heart Failure Care: Systematic Review and Subgroup Meta-Analysis," *Journal of Medical Internet Research* (22:11), p. e20032.

Dong, J. Q., Karhade, P. P., Rai, A., and Xu, S. X. 2021. "How Firms Make Information Technology Investment Decisions: Toward a Behavioral Agency Theory," *Journal of Management Information Systems* (38:1), pp. 29-58.

Du, K. 2015. "Research Note—Parenting New Acquisitions: Acquirers' Digital Resource Redeployment and Targets' Performance Improvement in the Us Hospital Industry," *Information Systems Research* (26:4), pp. 829-844.

Duran, P., Kammerlander, N., van Essen, M., and Zellweger, T. 2016. "Doing More with Less: Innovation Input and Output in Family Firms," *Academy of Management Journal* (59:4), pp. 1224-1264.

Eftekhari, S., Yaraghi, N., Gopal, R. D., and Ramesh, R. 2023. "Impact of Health Information Exchange Adoption on Referral Patterns," *Management Science* (69:3), pp. 1615-1638.

El-Rashidy, N., El-Sappagh, S., Islam, S. M. R., H, M. E.-B., and Abdelrazek, S. 2021. "Mobile Health in Remote Patient Monitoring for Chronic Diseases: Principles, Trends, and Challenges," *Diagnostics (Basel)* (11:4).

Elf, M., Flink, M., Nilsson, M., Tistad, M., von Koch, L., and Ytterberg, C. 2017. "The Case of Value-Based Healthcare for People Living with Complex Long-Term Conditions," *BMC Health Serv Res* (17:1), p. 24.

Elixhauser, A., Steiner, C., Harris, D. R., and Coffey, R. M. 1998. "Comorbidity Measures for Use with Administrative Data," *Medical care* (36:1), pp. 8-27.

Epstein, E., Patel, N., Maysent, K., and Taub, P. R. 2021. "Cardiac Rehab in the Covid Era and Beyond: Mhealth and Other Novel Opportunities," *Curr Cardiol Rep* (23:5), p. 42.

Everson, J., Lee, S.-Y. D., and Friedman, C. P. 2014. "Reliability and Validity of the American Hospital Association's National Longitudinal Survey of Health Information Technology Adoption," *Journal of the American Medical Informatics Association* (21:e2), pp. e257-e263.

Fan, W., Zhou, Q., Qiu, L., and Kumar, S. 2023. "Should Doctors Open Online Consultation Services? An Empirical Investigation of Their Impact on Offline Appointments," *Information Systems Research* (34:2), pp. 629-651.

Fontana, E. 2018. "Map: See the 2,599 Hospitals That Will Face Readmissions Penalties This Year." Retrieved 02/12/2024, 2024, from https://www.advisory.com/daily-briefing/2018/09/27/readmissions#:~:text=Roughly%2082%25%20of%20hospitals%20incurred,%24564%20estimate%20for%20FY%202018.

Furnari, S., Crilly, D., Misangyi, V. F., Greckhamer, T., Fiss, P. C., and Aguilera, R. V. 2021. "Capturing Causal Complexity: Heuristics for Configurational Theorizing," *Academy of Management Review* (46:4), pp. 778-799.

Gidwani, U. K., and Kini, A. S. 2013. "From the Coronary Care Unit to the Cardiovascular Intensive Care Unit: The Evolution of Cardiac Critical Care," *Cardiology Clinics* (31:4), pp. 485-492, vii.

Glynn, A. N., and Quinn, K. M. 2010. "An Introduction to the Augmented Inverse Propensity Weighted Estimator," *Political Analysis* (18:1), pp. 36-56.

Gong, G., Phillips, S. G., Hudson, C., Curti, D., and Philips, B. U. 2019. "Higher Us Rural Mortality Rates Linked to Socioeconomic Status, Physician Shortages, and Lack of Health Insurance," *Health Affairs* (38:12), pp. 2003-2010.

Gong, J., Liang, Y., and Ramasubbu, N. 2023. "Software-Vendor Diversification: A Source of Organizational Rigidity in Adversity?," *Journal of Management Information Systems* (40:2), pp. 338-365.

Goodman-Bacon, A. 2021. "Difference-in-Differences with Variation in Treatment Timing," *Journal of Econometrics* (225:2), pp. 254-277.

Gorbenko, K., Baim-Lance, A., Franzosa, E., Wurtz, H., Schiller, G., Masse, S., Ornstein, K. A., Federman, A., Levine, D. M., DeCherrie, L. V., Leff, B., and Siu, A. 2023. "A National Qualitative Study of Hospital-at-Home Implementation under the Cms Acute Hospital Care at Home Waiver," *Journal of American Geriatrics Society* (71:1), pp. 245-258.

Greenwood, B. N., Agarwal, R., Agarwal, R., and Gopal, A. 2017. "The When and Why of Abandonment: The Role of Organizational Differences in Medical Technology Life Cycles," *Management Science* (63:9), pp. 2948-2966.

Greve, H. R. 1998. "Performance, Aspirations, and Risky Organizational Change," *Administrative Science Quarterly* (43:1), pp. 58-86.

Greve, H. R. 2003. *Organizational Learning from Performance Feedback: A Behavioral Perspective on Innovation and Change*. Cambridge University Press.

Grossi, A., Hoxhaj, I., Gabutti, I., Specchia, M. L., Cicchetti, A., Boccia, S., and de Waure, C. 2021. "Hospital Contextual Factors Affecting the Implementation of Health Technologies: A Systematic Review," *BMC Health Services Research* (21:1), pp. 1-12.

Guo, F., Li, Y., Maruping, L. M., and Masli, A. 2023. "Complementarity between Investment in Information Technology (IT) and IT Human Resources: Implications for Different Types of Firm Innovation," *Information Systems Research* (34:3), pp. 1259-1275.

Hargittai, E., and Hinnant, A. 2008. "Digital Inequality: Differences in Young Adults' Use of the Internet," *Communication Research* (35:5), pp. 602-621.

Harris, J., Curtis, M., Sandalow, M., Hoagland, G. W., and Serafini, M. W. 2024. "The Future of Remote Patient Monitoring," Bipartisan Policy Center.

Harvey, M., and Seiler, A. 2022. "Challenges in Managing a Remote Monitoring Device Clinic," *Heart Rhythm O2* (3:1), pp. 3-7.

Hatef, E., Ma, X., Shaikh, Y., Kharrazi, H., Weiner, J. P., and Gaskin, D. J. 2021. "Internet Access, Social Risk Factors, and Web-Based Social Support Seeking Behavior: Assessing Correlates of the "Digital Divide" across Neighborhoods in the State of Maryland," *Journal of Medical Systems* (45:11), p. 94.

Hattab, Z., Doherty, E., Ryan, A. M., and O'Neill, S. 2024. "Heterogeneity within the Oregon Health Insurance Experiment: An Application of Causal Forests," *PLoS One* (19:1), p. e0297205.

Havakhor, T., Sabherwal, R., Steelman, Z. R., and Sabherwal, S. 2019. "Relationships between Information Technology and Other Investments: A Contingent Interaction Model," *Information Systems Research* (30:1), pp. 291-305.

Health, U. 2020. "Remote Patient Monitoring Programs." Retrieved 10/10/2020, from https://www.uclahealth.org/telehealth/remote-patient-monitoring

HHS, T. U. D. o. H. a. H. S. 2023. "Consumer Alert: Remote Patient Monitoring." from https://oig.hhs.gov/fraud/consumer-alerts/consumer-alert-remote-monitoring/

Hill, T. D., Davis, A. P., Roos, J. M., and French, M. T. 2020. "Limitations of Fixed-Effects Models for Panel Data," *Sociological Perspectives* (63:3), pp. 357-369.

Hitt, M. A., Xu, K., and Carnes, C. M. 2016. "Resource Based Theory in Operations Management Research," *Journal of Operations Management* (41:1), pp. 77-94.

Ho, J., Tian, F., Wu, A., and Xu, S. X. 2017. "Seeking Value through Deviation? Economic Impacts of IT Overinvestment and Underinvestment," *Information Systems Research* (28:4), pp. 850-862.

Hsieh, J. J. P.-A., Rai, A., and Keil, M. 2011. "Addressing Digital Inequality for the Socioeconomically Disadvantaged through Government Initiatives: Forms of Capital That Affect Ict Utilization," *Information Systems Research* (22:2), pp. 233-253.

Hsieh, J. P.-A., Rai, A., and Keil, M. 2008. "Understanding Digital Inequality: Comparing Continued Use Behavioral Models of the Socio-Economically Advantaged and Disadvantaged," *MIS Quarterly* (32), pp. 97-126.

Hu, A. 2023. "Heterogeneous Treatment Effects Analysis for Social Scientists: A Review," *Social Science Research* (109), p. 102810.

Hu, H., Wang, N., and Liang, H. 2023. "Effects of Intellectual and Social Alignment on Organizational Agility: A Configurational Theory Approach," *Journal of the Association for Information Systems* (24:2), pp. 490-529.

Iacus, S. M., King, G., and Porro, G. 2012. "Causal Inference without Balance Checking: Coarsened Exact Matching," *Political Analysis* (20:1), pp. 1-24.

Imran, T. F., Wang, N., Zombeck, S., and Balady, G. J. 2021. "Mobile Technology Improves Adherence to Cardiac Rehabilitation: A Propensity Score-Matched Study," *Journal of the American Heart Association* (10:15), p. e020482.

Iyer, D. N., and Miller, K. D. 2008. "Performance Feedback, Slack, and the Timing of Acquisitions," *Academy of Management Journal* (51:4), pp. 808-822.

Janakiraman, R., Park, E., M. Demirezen, E., and Kumar, S. 2023. "The Effects of Health Information Exchange Access on Healthcare Quality and Efficiency: An Empirical Investigation," *Management Science* (69:2), pp. 791-811.

Jha, A. K., DesRoches, C. M., Campbell, E. G., Donelan, K., Rao, S. R., Ferris, T. G., Shields, A., Rosenbaum, S., and Blumenthal, D. 2009. "Use of Electronic Health Records in Us Hospitals," *New England Journal of Medicine* (360:16), pp. 1628-1638.

Jiang, J., and Cameron, A.-F. 2020. "IT-Enabled Self-Monitoring for Chronic Disease Self-Management: An Interdisciplinary Review," *MIS Quarterly* (44:1), pp. 451-508.

Joynt Maddox, K., Bleser, W. K., Crook, H. L., Nelson, A. J., Hamilton Lopez, M., Saunders, R. S., McClellan, M. B., Brown, N., and American Heart Association Value-Based Models Learning, C. 2020. "Advancing Value-Based Models for Heart Failure: A Call to Action from the Value in Healthcare Initiative's Value-Based Models Learning Collaborative," *Circulation: Cardiovascular Quality and Outcomes* (13:5), p. e006483.

Karahanna, E., Chen, A., Liu, Q. B., and Serrano, C. 2019. "Capitalizing on Health Information Technology to Enable Digital Advantage in Us Hospitals," *MIS Quarterly* (43:1), pp. 113-140.

Karhade, P., and Dong, J. Q. 2021. "Innovation Outcomes of Digitally Enabled Collaborative Problemistic Search Capability," *MIS Quarterly* (45:2), pp. 693-718.

Kauppi, K., and Taponen, S. 2022. "Collaborators, Supplementers, Purchasers and Privatizers - Profiling the Social and Health Care Delivery Forms of Finnish Municipalities through Cluster Analysis," *Public Management Review*), pp. 1-24.

Khan, H., Greene, S. J., Fonarow, G. C., Kalogeropoulos, A. P., Ambrosy, A. P., Maggioni, A. P., Zannad, F., Konstam, M. A., Swedberg, K., Yancy, C. W., Gheorghiade, M., Butler, J., and Investigators, E. T. 2015. "Length of Hospital Stay and 30-Day Readmission Following Heart Failure Hospitalization: Insights from the Everest Trial," *European Journal of Heart Failure* (17:10), pp. 1022-1031.

Kilgore, M., Patel, H. K., Kielhorn, A., Maya, J. F., and Sharma, P. 2017. "Economic Burden of Hospitalizations of Medicare Beneficiaries with Heart Failure," *Risk Management and Healthcare Policy* (10), pp. 63-70.

Kimberly, J. R., and Evanisko, M. J. 1981. "Organizational Innovation: The Influence of Individual, Organizational, and Contextual Factors on Hospital Adoption of Technological and Administrative Innovations," *Academy of Management Journal* (24:4), pp. 689-713.

King-Dailey, K., Frazier, S., Bressler, S., and King-Wilson, J. 2022. "The Role of Nurse Practitioners in the Management of Heart Failure Patients and Programs," *Current Cardiology Reports* (24:12), pp. 1945-1956.

Kitagawa, T., and Tetenov, A. 2018. "Who Should Be Treated? Empirical Welfare Maximization Methods for Treatment Choice," *Econometrica* (86:2), pp. 591-616.

Koehler, F., Koehler, K., Prescher, S., Kirwan, B. A., Wegscheider, K., Vettorazzi, E., Lezius, S., Winkler, S., Moeller, V., Fiss, G., Schleder, J., Koehler, M., Zugck, C., Stork, S., Butter, C., Prondzinsky, R., Spethmann, S., Angermann, C., Stangl, V., Halle, M., von Haehling, S., Dreger, H., Stangl, K., Deckwart, O., and Anker, S. D. 2020. "Mortality and Morbidity 1 Year after Stopping a Remote Patient Management Intervention: Extended Follow-up Results from the Telemedical Interventional Management in Patients with Heart Failure II (Tim-Hf2) Randomised Trial," *Lancet Digital Health* (2:1), pp. e16-e24.

Kohli, R., and Tan, S. S.-L. 2016. "Electronic Health Records: How Can IS Researchers Contribute to Transforming Healthcare?," *MIS Quarterly* (40:3), pp. 553-573.

Komajda, M. 2015. "Current Challenges in the Management of Heart Failure," *Circulation Journal* (79:5), pp. 948-953.

Kreif, N., DiazOrdaz, K., Moreno-Serra, R., Mirelman, A., Hidayat, T., and Suhrcke, M. 2021. "Estimating Heterogeneous Policy Impacts Using Causal Machine Learning: A Case Study of Health Insurance Reform in Indonesia," *Health Services and Outcomes Research Methodology* (22:2), pp. 192-227.

Kumar, A., Iqbal, K., Shariff, M., Majmundar, M., and Kalra, A. 2024. "Social Associations and Cardiovascular Mortality in the United States Counties, 2016 to 2020," *BMC Cardiovascular Disorders* (24:1), p. 127.

Lear, S. A. 2018. "The Delivery of Cardiac Rehabilitation Using Communications Technologies: The "Virtual" Cardiac Rehabilitation Program," *Canadian Journal of Cardiology* (34:10 Suppl 2), pp. S278-S283.

Lee, S. J., Venkataraman, S., Heim, G. R., Roth, A. V., and Chilingerian, J. 2019. "Impact of the Value-Based Purchasing Program on Hospital Operations Outcomes: An Econometric Analysis," *Journal of Operations Management* (66:1-2), pp. 151-175.

Leon, M. A., Pannunzio, V., and Kleinsmann, M. 2022. "The Impact of Perioperative Remote Patient Monitoring on Clinical Staff Workflows: Scoping Review," *JMIR Human Factors* (9:2), p. e37204.

Leung, R. C. 2012. "Health Information Technology and Dynamic Capabilities," *Health Care Management Review* (37:1), pp. 43-53.

Levine, D. M., DeCherrie, L. V., Siu, A. L., and Leff, B. 2021. "Early Uptake of the Acute Hospital Care at Home Waiver," *Annals of Internal Medicine* (174:12), pp. 1772-1774.

Li, F., Morgan, K. L., and Zaslavsky, A. M. 2018. "Balancing Covariates Via Propensity Score Weighting," *Journal of the American Statistical Association* (113:521), pp. 390-400.

Li, L., Chen, L., Yan, J., Xu, C., and Jiang, N. 2023. "How Does Technological Opportunism Affect Firm Performance? The Mediating Role of Resource Orchestration," *Journal of Business Research* (166).

Li, X., Rai, A., and Krishnan, G. 2020. "Designing Cost-Effective Telemedicine Camps for Underprivileged Individuals in Less Developed Countries: A Decomposed Affordance-Effectivity Framework," *Journal of the Association for Information Systems* (21:5), pp. 1279-1312.

Li, Y., Lu, L. X., Lu, S. F., and Chen, J. 2022. "The Value of Health Information Technology Interoperability: Evidence from Interhospital Transfer of Heart Attack Patients," *Manufacturing & Service Operations Management* (24:2), pp. 827-845.

Lin, Y.-K., Lin, M., and Chen, H. 2019. "Do Electronic Health Records Affect Quality of Care? Evidence from the Hitech Act," *Information Systems Research* (30:1), pp. 306-318.

Loughran, J., Puthawala, T., Sutton, B. S., Brown, L. E., Pronovost, P. J., and DeFilippis, A. P. 2017. "The Cardiovascular Intensive Care Unit-an Evolving Model for Health Care Delivery," *Journal of Intensive Care Medicine* (32:2), pp. 116-123.

Lu, S. F., Rui, H., and Seidmann, A. 2018. "Does Technology Substitute for Nurses? Staffing Decisions in Nursing Homes," *Management Science* (64:4), pp. 1842-1859.

Lythreatis, S., Singh, S. K., and El-Kassar, A.-N. 2022. "The Digital Divide: A Review and Future Research Agenda," *Technological Forecasting and Social Change* (175).

Makutonin, M., Dare, J., Heekin, M., Salancy, A., Hood, C., and Dominguez, L. W. 2023. "Remote Patient Monitoring for Hypertension: Feasibility and Outcomes of a Clinic-Based Pilot in a Minority Population," *Journal of Primary Care & Community Health* (14), p. 21501319231204586.

Manemann, S. M., Chamberlain, A. M., Roger, V. L., Griffin, J. M., Boyd, C. M., Cudjoe, T. K. M., Jensen, D., Weston, S. A., Fabbri, M., Jiang, R., and Finney Rutten, L. J. 2018. "Perceived Social Isolation and Outcomes in Patients with Heart Failure," *Journal of the American Heart Association* (7:11).

Marafino, B. J., Schuler, A., Liu, V. X., Escobar, G. J., and Baiocchi, M. 2020. "Predicting Preventable Hospital Readmissions with Causal Machine Learning," *Health Services Research* (55:6), pp. 993-1002.

Mastoris, I., DeFilippis, E. M., Martyn, T., Morris, A. A., Van Spall, H. G., and Sauer, A. J. 2023. "Remote Patient Monitoring for Patients with Heart Failure: Sex- and Race-Based Disparities and Opportunities," *Cardiac Failure Review* (9), p. e02.

McCullough, J. S., Casey, M., Moscovice, I., and Prasad, S. 2010. "The Effect of Health Information Technology on Quality in Us Hospitals," *Health Affairs* (29:4), pp. 647-654.

McKenna, R. M., Dwyer, D., and Rizzo, J. A. 2018. "Is HIT a Hit? The Impact of Health Information Technology on Inpatient Hospital Outcomes," *Applied Economics* (50:27), pp. 3016-3028.

Mesquita, E. T., Jorge, A. J. L., Rabelo, L. M., and Souza Jr, C. V. 2016. "Understanding Hospitalization in Patients with Heart Failure," *International Journal of Cardiovascular Sciences*).

Meyer, A. D., Tsui, A. S., and Hinings, C. R. 1993. "Configurational Approaches to Organizational Analysis," *Academy of Management Journal* (36:6), pp. 1175-1195.

Mishra, A. N., Tao, Y., Keil, M., and Oh, J.-h. 2022. "Functional IT Complementarity and Hospital Performance in the United States: A Longitudinal Investigation," *Information Systems Research* (33:1), pp. 55-75.

Mithas, S., Tafti, A., Bardhan, I., and Goh, J. M. 2012. "Information Technology and Firm Profitability: Mechanisms and Empirical Evidence," *MIS Quarterly* (36:1), pp. 205-224.

Muniyappa, A. N., Raitt, M. H., Judson, G. L., Shen, H., Tarasovsky, G., Whooley, M. A., and Dhruva, S. S. 2022. "Factors Associated with Remote Monitoring Adherence for Cardiovascular Implantable Electronic Devices," *Heart Rhythm* (19:9), pp. 1499-1507.

Nakamura, N., Koga, T., and Iseki, H. 2014. "A Meta-Analysis of Remote Patient Monitoring for Chronic Heart Failure Patients," *Journal of Telemedicine and Telecare* (20:1), pp. 11-17.

Nakayama, A., Takayama, N., Kobayashi, M., Hyodo, K., Maeshima, N., Takayuki, F., Morita, H., and Komuro, I. 2020. "Remote Cardiac Rehabilitation Is a Good Alternative of Outpatient Cardiac Rehabilitation in the Covid-19 Era," *Environmental Health and Preventive Medicine* (25:1), p. 48.

Nigam, A., Huising, R., and Golden, B. 2016. "Explaining the Selection of Routines for Change During Organizational Search," *Administrative Science Quarterly* (61:4), pp. 551-583.

Oh, J.-h. C., Zheng, Z. E., and Bardhan, I. R. 2018. "Sooner or Later? Health Information Technology, Length of Stay, and Readmission Risk," *Production and Operations Management* (27:11), pp. 2038-2053.

Oliver, C. 1997. "Sustainable Competitive Advantage: Combining Institutional and Resource-Based Views," *Strategic Management Journal* (18:9), pp. 697-713.

Pan, S. L., Cui, M., and Qian, J. 2020. "Information Resource Orchestration During the Covid-19 Pandemic: A Study of Community Lockdowns in China," *International Journal of Information Management* (54), p. 102143.

Pandor, A., Gomersall, T., Stevens, J. W., Wang, J., Al-Mohammad, A., Bakhai, A., Cleland, J. G., Cowie, M. R., and Wong, R. 2013. "Remote Monitoring after Recent Hospital Discharge in Patients with Heart Failure: A Systematic Review and Network Meta-Analysis," *Heart* (99:23), pp. 1717-1726.

Park, Y., and Mithas, S. 2020. "Organized Complexity of Digital Business Strategy: A Configurational Perspective," *MIS Quarterly* (44:1), pp. 85-127.

Paul, J. A., Quosigk, B., and MacDonald, L. 2020. "Does Hospital Status Affect Performance?," *Nonprofit and Voluntary Sector Quarterly* (49:2), pp. 229-251.

Pearl, R. 2023. "What Kaiser's Acquisition of Geisinger Means for Us All." from https://www.forbes.com/sites/robertpearl/2023/05/31/what-kaisers-acquisition-of-geisinger-means-for-us-all/?sh=21c5e6265796

Peters, C., Blohm, I., and Leimeister, J. M. 2015. "Anatomy of Successful Business Models for Complex Services: Insights from the Telemedicine Field," *Journal of Management Information Systems* (32:3), pp. 75-104.

Pethig, F., and Kroenung, J. 2019. "Specialized Information Systems for the Digitallydisadvantaged," *Journal of the Association for Information Systems* (20:10), pp. 1412-1446.

Polikandrioti, M., Goudevenos, J., Michalis, L. K., Koutelekos, J., Kyristi, H., Tzialas, D., and Elisaf, M. 2015. "Factors Associated with Depression and Anxiety of Hospitalized Patients with Heart Failure," *Hellenic Journal of Cardiology* (56:1), pp. 26-35.

Porter, M. E., and Lee, T. H. 2013. "The Strategy That Will Fix Health Care," *Harvard Business Review* (91:12), pp. 24-24.

Posen, H. E., Keil, T., Kim, S., and Meissner, F. D. 2018. "Renewing Research on Problemistic Search—a Review and Research Agenda," *Academy of Management Annals* (12:1), pp. 208-251.

Pye, J., Rai, A., and Dong, J. Q. 2024. "How Hospitals Differentiate Health Information Technology Portfolios for Clinical Care Efficiency: Insights from the Hitech Act," *Information Systems Research* (0:0).

Qiu, L., Kumar, S., Sen, A., and Sinha, A. P. 2022. "Impact of the Hospital Readmission Reduction Program on Hospital Readmission and Mortality: An Economic Analysis," *Production and Operations Management* (31:5), pp. 2341-2360.

Raab, J., Mannak, R. S., and Cambre, B. 2013. "Combining Structure, Governance, and Context: A Configurational Approach to Network Effectiveness," *Journal of Public Administration Research and Theory* (25:2), pp. 479-511.

Racherla, P., and Mandviwalla, M. 2013. "Moving from Access to Use of the Information Infrastructure: A Multilevel Sociotechnical Framework," *Information Systems Research* (24:3), pp. 709-730.

Rajan, B., Seidmann, A., and Dorsey, E. R. 2013. "The Competitive Business Impact of Using Telemedicine for the Treatment of Patients with Chronic Conditions," *Journal of Management Information Systems* (30:2), pp. 127-158.

Rao, V. U., Bhasin, A., Vargas, J., Jr., and Arun Kumar, V. 2022. "A Multidisciplinary Approach to Heart Failure Care in the Hospital: Improving the Patient Journey," *Hospital Practice* (50:3), pp. 170-182.

Ravichandran, T., Han, S., and Hasan, I. 2009. "Effects of Institutional Pressures on Information Technology Investments: An Empirical Investigation," *IEEE Transactions on Engineering Management* (56:4), pp. 677-691.

Ray, J. C., and Kusumoto, F. 2016. "The Transition to Value-Based Care," *J Interv Card Electrophysiol* (47:1), pp. 61-68.

Rethy, L. B., McCabe, M. E., Kershaw, K. N., Ahmad, F. S., Lagu, T., Pool, L. R., and Khan, S. S. 2021. "Neighborhood Poverty and Incident Heart Failure: An Analysis of Electronic Health Records from 2005 to 2018," *Journal of General Internal Medicine* (36:12), pp. 3719-3727.

Rishika, R., Kumar, A., Janakiraman, R., and Bezawada, R. 2013. "The Effect of Customers' Social Media Participation on Customer Visit Frequency and Profitability: An Empirical Investigation," *Information Systems Research* (24:1), pp. 108-127.

Robinson, P. M. 1988. "Root-N-Consistent Semiparametric Regression," *Econometrica: Journal of the Econometric Society* (56:4), pp. 931-954.

Rosenbaum, P. R., and Rubin, D. B. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika* (70:1), pp. 41-55.

Ruan, T., Xu, M., Zhu, L., and Ding, Y. 2023. "Nurse-Coordinated Home-Based Cardiac Rehabilitation for Patients with Heart Failure: A Scoping Review," *International Journal of Nursing Sciences* (10:4), pp. 435-445.

Ryan, A. M., Burgess Jr, J. F., and Dimick, J. B. 2015. "Why We Should Not Be Indifferent to Specification Choices for Difference-in-Differences," *Health Services Research* (50:4), pp. 1211-1235.

Saeed, S. A., and Masters, R. M. 2021. "Disparities in Health Care and the Digital Divide," *Current Psychiatry Reports* (23:9), p. 61.

Saito, H., Kagiyama, N., Nagano, N., Matsumoto, K., Yoshioka, K., Endo, Y., Hayashida, A., and Matsue, Y. 2019. "Social Isolation Is Associated with 90-Day Rehospitalization Due to Heart Failure," *European Journal of Cardiovascular Nursing* (18:1), pp. 16-20.

Salge, T. O. 2010. "A Behavioral Model of Innovative Search: Evidence from Public Hospital Services," *Journal of Public Administration Research and Theory* (21:1), pp. 181-210.

Salge, T. O. 2012. "The Temporal Trajectories of Innovative Search: Insights from Public Hospital Services," *Research Policy* (41:4), pp. 720-733.

Salge, T. O., Kohli, R., and Barrett, M. 2015. "Investing in Information Systems," *MIS Quarterly* (39:1), pp. 61-90.

Sandberg, J., Mathiassen, L., and Napier, N. 2014. "Digital Options Theory for IT Capability Investment," *Journal of the Association for Information Systems* (15:7), p. 1.

Segar, M. W., Keshvani, N., Rao, S., Fonarow, G. C., Das, S. R., and Pandey, A. 2022. "Race, Social Determinants of Health, and Length of Stay among Hospitalized Patients with Heart Failure: An Analysis from the Get with the Guidelines-Heart Failure Registry," *Circulation: Heart Failure* (15:11), p. e009401.

Serrano, L. P., Maita, K. C., Avila, F. R., Torres-Guzman, R. A., Garcia, J. P., Eldaly, A. S., Haider, C. R., Felton, C. L., Paulson, M. R., and Maniaci, M. J. 2023. "Benefits and Challenges of Remote Patient Monitoring as Perceived by Health Care Practitioners: A Systematic Review," *The Permanente Journal* (27:4), p. 100.

Sevilla-Cazes, J., Ahmad, F. S., Bowles, K. H., Jaskowiak, A., Gallagher, T., Goldberg, L. R., Kangovi, S., Alexander, M., Riegel, B., Barg, F. K., and Kimmel, S. E. 2018. "Heart Failure Home Management Challenges and Reasons for Readmission: A Qualitative Study to Understand the Patient's Perspective," *Journal of General Internal Medicine* (33:10), pp. 1700-1707.

Shafie, A. A., Tan, Y. P., and Ng, C. H. 2018. "Systematic Review of Economic Burden of Heart Failure," *Heart Failure Reviews* (23:1), pp. 131-145.

Shah, A., Hussain-Shamsy, N., Strudwick, G., Sockalingam, S., Nolan, R. P., and Seto, E. 2022. "Digital Health Interventions for Depression and Anxiety among People with Chronic Conditions: Scoping Review," *Journal of Medical Internet Research* (24:9), p. e38030.

Shah, D., Simms, K., Barksdale, D., and Wu, J.-R. 2015. "Improving Medication Adherence of Patients with Chronic Heart Failure: Challenges and Solutions," *Research Reports in Clinical Cardiology* (6).

Shah, R., Kedia, S., Rawooth, M., Chokalingam, K., Kadambi, P., and Parchani, G. 2023. "Remote Monitoring in Heart Failure: Recent Trends and Future Perspectives," *Medical Research Archives* (11:1).

Sharma, N., Schwendimann, R., Endrich, O., Ausserhofer, D., and Simon, M. 2021. "Comparing Charlson and Elixhauser Comorbidity Indices with Different Weightings to Predict in-Hospital Mortality: An Analysis of National Inpatient Data," *BMC Health Services Research* (21:1), p. 13.

Sherer, S. A., Meyerhoefer, C. D., and Peng, L. 2016. "Applying Institutional Theory to the Adoption of Electronic Health Records in the Us," *Information & Management* (53:5), pp. 570-580.

Shirey, T. E., Hu, Y., Ko, Y. A., Nayak, A., Udeshi, E., Patel, S., and Morris, A. A. 2021. "Relation of Neighborhood Disadvantage to Heart Failure Symptoms and Hospitalizations," *The American Journal of Cardiology* (140), pp. 83-90.

Siddique, S. M., Tipton, K., Leas, B., Greysen, S. R., Mull, N. K., Lane-Fall, M., McShea, K., and Tsou, A. Y. 2021. "Interventions to Reduce Hospital Length of Stay in High-Risk Populations: A Systematic Review," *JAMA Network Open* (4:9), p. e2125846.

Singh, R., Mathiassen, L., Stachura, M. E., and Astapova, E. V. 2011. "Dynamic Capabilities in Home Health: IT-Enabled Transformation of Post-Acute Care," *Journal of the Association for Information Systems* (12:2), pp. 163-188.

Singh, R., Mindel, V., and Mathiassen, L. 2017. "IT-Enabled Revenue Cycle Transformation in Resource-Constrained Hospitals: A Collaborative Digital Options Inquiry," *Journal of Management Information Systems* (34:3), pp. 695-726.

Sirmon, D. G., Barney, J. B., Ketchen, D. J., Wright, M., Hitt, M. A., Ireland, R. D., and Gilbert, B. A. 2010. "Resource Orchestration to Create Competitive Advantage," *Journal of Management* (37:5), pp. 1390-1412.

Sirmon, D. G., and Hitt, M. A. 2009. "Contingencies within Dynamic Managerial Capabilities: Interdependent Effects of Resource Investment and Deployment on Firm Performance," *Strategic Management Journal* (30:13), pp. 1375-1394.

Son, J., Flatley Brennan, P., and Zhou, S. 2020. "A Data Analytics Framework for Smart Asthma Management Based on Remote Health Information Systems with Bluetooth-Enabled Personal Inhalers," *MIS Quarterly* (44:1), pp. 285-303.

Song, Z., Johnston, R. M., and Ng, C. P. 2021. "Equitable Healthcare Access During the Pandemic: The Impact of Digital Divide and Other Sociodemographic and Systemic Factors," *Applied Research in Artificial Intelligence and Cloud Computing* (4:1), pp. 19-33.

Spetz, J., and Maiuro, L. S. 2004. "Measuring Levels of Technology in Hospitals," *The Quarterly Review of Economics and Finance* (44:3), pp. 430-447.

Srinivasan, R., Lilien, G. L., and Rangaswamy, A. 2002. "Technological Opportunism and Radical Technology Adoption: An Application to E-Business," *Journal of Marketing* (66:3), pp. 47-60.

Srivastava, S. C., and Shainesh, G. 2015. "Bridging the Service Divide through Digitally Enabled Service Innovations: Evidence from Indian Healthcare Service Providers," *MIS Quarterly* (39:1), pp. 245-267.

Steelman, Z. R., Havakhor, T., Sabherwal, R., and Sabherwal, S. 2019. "Performance Consequences of Information Technology Investments: Implications of Emphasizing New or Current Information Technologies," *Information Systems Research* (30:1), pp. 204-218.

Steinhauser, S., Doblinger, C., and Hüsig, S. 2020. "The Relative Role of Digital Complementary Assets and Regulation in Discontinuous Telemedicine Innovation in European Hospitals," *Journal of Management Information Systems* (37:4), pp. 1155-1183.

Sun, L., and Abraham, S. 2021. "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects," *Journal of Econometrics* (225:2), pp. 175-199.

Sun, S., Lu, S. F., and Rui, H. 2020. "Does Telemedicine Reduce Emergency Room Congestion? Evidence from New York State," *Information Systems Research* (31:3), pp. 972-986.

Sutton, J. 1991. *Sunk Costs and Market Structure: Price Competition, Advertising, and the Evolution of Concentration*. MIT press.

Taylor, M. L., Thomas, E. E., Snoswell, C. L., Smith, A. C., and Caffery, L. J. 2021. "Does Remote Patient Monitoring Reduce Acute Care Use? A Systematic Review," *BMJ Open* (11:3), p. e040232.

Thompson, S., Whitaker, J., Kohli, R., and Jones, C. 2020. "Chronic Disease Management: How IT and Analytics Create Healthcare Value through the Temporal Displacement of Care," *MIS Quarterly* (44:1), pp. 227-256.

Turedi, S., and Zhu, H. 2019. "How to Generate More Value from IT: The Interplay of IT Investment, Decision Making Structure, and Senior Management Involvement in IT Governance," *Communications of the Association for Information Systems* (44:1), pp. 511-536.

Turner, K., Bobonis Babilonia, M., Naso, C., Nguyen, O., Gonzalez, B. D., Oswald, L. B., Robinson, E., Elston Lafata, J., Ferguson, R. J., Alishahi Tabriz, A., Patel, K. B., Hallanger-Johnson, J., Aldawoodi, N., Hong, Y. R., Jim, H. S. L., and Spiess, P. E. 2022. "Health Care Providers' and Professionals' Experiences with Telehealth Oncology Implementation During the Covid-19 Pandemic: A Qualitative Study," *Journal of Medical Internet Research* (24:1), p. e29635.

Turner, K., Jo, A., Wei, G., Tabriz, A. A., Clary, A., and Jim, H. S. 2021. "Sharing Patient-Generated Data with Healthcare Providers: Findings from a 2019 National Survey," *Journal of the American Medical Informatics Association* (28:2), pp. 371-376.

Vandenberk, B., and Raj, S. R. 2023. "Remote Patient Monitoring: What Have We Learned and Where Are We Going?," *Current Cardiovascular Risk Reports* (17:6), pp. 103-115.

Vassilakopoulou, P., and Hustad, E. 2021. "Bridging Digital Divides: A Literature Review and Research Agenda for Information Systems Research," *Information Systems Frontiers* (25:3), pp. 1-15.

Vegesna, A., Tran, M., Angelaccio, M., and Arcona, S. 2017. "Remote Patient Monitoring Via Non-Invasive Digital Technologies: A Systematic Review," *Telemedicine and e-Health* (23:1), pp. 3-17.

Venkatesh, V., and Sykes, T. A. 2013. "Digital Divide Initiative Success in Developing Countries: A Longitudinal Field Study in a Village in India," *Information Systems Research* (24:2), pp. 239-260.

Venkatesh, V., Zhang, X., and Sykes, T. A. 2011. "“Doctors Do Too Little Technology”: A Longitudinal Field Study of an Electronic Healthcare System Implementation," *Information Systems Research* (22:3), pp. 523-546.

Vest, J. R., Freedman, S., Unruh, M. A., Bako, A. T., and Simon, K. 2022. "Strategic Use of Health Information Exchange and Market Share, Payer Mix, and Operating Margins," *Health Care Management Review* (47:1), pp. 28-36.

Vest, J. R., Unruh, M. A., Freedman, S., and Simon, K. 2019. "Health Systems’ Use of Enterprise Health Information Exchange Vs Single Electronic Health Record Vendor Environments and Unplanned Readmissions," *Journal of the American Medical Informatics Association* (26:10), pp. 989-998.

Vong, W.-T., Kong, M. L., Lai, C. C., Then, P. H., and Teo, T.-H. 2017. "Investigating the Roles of Knowledge Management Practices in Empowering Rural Youth to Bridge the Digital Divide in Rural Sarawak," *Journal of Integrated Design and Process Science* (21:1), pp. 61-79.

Wager, S., and Athey, S. 2018. "Estimation and Inference of Heterogeneous Treatment Effects Using Random Forests," *Journal of the American Statistical Association* (113:523), pp. 1228-1242.

Wang, G. 2022. "The Effect of Medicaid Expansion on Wait Time in the Emergency Department," *Management Science* (68:9), pp. 6648-6665.

Wei, K.-K., Teo, H.-H., Chan, H. C., and Tan, B. C. Y. 2011. "Conceptualizing and Testing a Social Cognitive Model of the Digital Divide," *Information Systems Research* (22:1), pp. 170-187.

White-Williams, C., Rossi, L. P., Bittner, V. A., Driscoll, A., Durant, R. W., Granger, B. B., Graven, L. J., Kitko, L., Newlin, K., Shirey, M., American Heart Association Council on, C., Stroke, N., Council on Clinical, C., Council on, E., and Prevention. 2020. "Addressing Social Determinants of Health in the Care of Patients with Heart Failure: A Scientific Statement from the American Heart Association," *Circulation* (141:22), pp. e841-e863.

Whitehead, D., and Conley, J. 2023. "The Next Frontier of Remote Patient Monitoring: Hospital at Home," *Journal of Medical Internet Research* (25), p. e42335.

Whitman, E. 2016. "Great Job Reducing Readmissions, Hospitals (but It's About to Get Harder)." Retrieved 4/24/2022, 2022, from https://www.modernhealthcare.com/article/20160917/MAGAZINE/309179963/great-job-reducing-readmissions-hospitals-but-it-s-about-to-get-harder#:~:text=Medicare%20views%20hospital%20readmission%20rates,of%20care%20a%20patient%20receives.

Williams, D. R., and Wyatt, R. 2015. "Racial Bias in Health Care and Health: Challenges and Opportunities," *JAMA* (314:6), pp. 555-556.

Wongvibulsin, S., Habeos, E. E., Huynh, P. P., Xun, H., Shan, R., Porosnicu Rodriguez, K. A., Wang, J., Gandapur, Y. K., Osuji, N., Shah, L. M., Spaulding, E. M., Hung, G., Knowles, K., Yang, W. E., Marvel, F. A., Levin, E., Maron, D. J., Gordon, N. F., and Martin, S. S. 2021. "Digital Health Interventions for Cardiac Rehabilitation: Systematic Literature Review," *Journal of Medical Internet Research* (23:2), p. e18773.

Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*. MIT press.

Xin, M., and Choudhary, V. 2019. "IT Investment under Competition: The Role of Implementation Failure," *Management Science* (65:4), pp. 1909-1925.

Yaraghi, N., Ye Du, A., Sharman, R., Gopal, R. D., and Ramesh, R. 2015. "Health Information Exchange as a Multisided Platform: Adoption, Usage, and Practice Involvement in Service Co-Production," *Information Systems Research* (26:1), pp. 1-18.

Ye, Y., Yu, W., and Nason, R. 2020. "Performance Feedback Persistence: Comparative Effects of Historical Versus Peer Performance Feedback on Innovative Search," *Journal of Management* (47:4), pp. 1053-1081.

Yeo, Y. H., Wang, M., He, X., Lv, F., Zhang, Y., Zu, J., Li, M., Jiao, Y., Ebinger, J. E., and Patel, J. K. 2023. "Excess Risk for Acute Myocardial Infarction Mortality During the Covid-19 Pandemic," *Journal of Medical Virology* (95:1), p. e28187.

Yu, W., Liu, Q., Zhao, G., and Song, Y. 2022. "Exploring the Effects of Data-Driven Hospital Operations on Operational Performance from the Resource Orchestration Theory Perspective," *IEEE Transactions on Engineering Management* (70:8), pp. 1-13.

Zahra, S. A. 2021. "The Resource-Based View, Resourcefulness, and Resource Management in Startup Firms: A Proposed Research Agenda," *Journal of Management* (47:7), pp. 1841-1860.

Zhang, D. J., Gurvich, I., Van Mieghem, J. A., Park, E., Young, R. S., and Williams, M. V. 2016. "Hospital Readmissions Reduction Program: An Economic and Operational Analysis," *Management Science* (62:11), pp. 3351-3371.

Zhang, W., and Ram, S. 2020. "A Comprehensive Analysis of Triggers and Risk Factors for Asthma Based on Machine Learning and Large Heterogeneous Data Sources," *MIS Quarterly* (44:1), pp. 305-349.

Zhao, M., Hamadi, H., Rob Haley, D., White-Williams, C., Liu, X., and Spaulding, A. 2019. "The Relationship between Health Information Technology Laboratory Tracking Systems and Hospital Financial Performance and Quality," *Hospital Topics* (97:3), pp. 99-106.

Zhao, Y., Zhang, T., Dasgupta, R. K., and Xia, R. 2022. "Narrowing the Age-Based Digital Divide: Developing Digital Capability through Social Activities," *Information Systems Journal* (33:2), pp. 268-298.

Zhou, C., Hao, Y., Lan, Y., and Li, W. 2023. "To Introduce or Not? Strategic Analysis of Hospital Operations with Telemedicine," *European Journal of Operational Research* (304:1), pp. 292-307.