HEALTH INFORMATION EXCHANGE USE IN PRIMARY CARE

Nathan Calvert Apathy

Submitted to the faculty of the University Graduate School
in partial fulfillment of the requirements
for the degree
Doctor of Philosophy
in the Richard M. Fairbanks School of Public Health,
Indiana University

August 2020

Accepted by the Graduate Faculty of Indiana University, in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

Doctoral Committee

Christopher A. Harle, MS, PhD, Co-Chair

Joshua R. Vest, MPH, PhD, Co-Chair

Justin Blackburn, MPH, PhD

June 25, 2020

Julia Adler-Milstein, PhD

Brian E. Dixon, MPA, PhD

DEDICATION

Dedicated to my dad

Andy Apathy

Thank you for being there in the moments I most needed you

Your whole life lies ahead
It's just around the bend

So when the sun is coming up and you go
And there's still so many things you don't know
Don't you look back, I've no doubt that I
Will see you on the road

When the world's laying you low
Why don't you let me carry your load?
When things get bad you know you have a friend
All along the road

And I would love it sometime
If you would walk at my side
Going I don't know where to sing beneath the stars

"On The Road," Keane

ACKNOWLEDGEMENTS

While I may be listed as sole author, this was far from a solitary effort. I am eternally grateful to the communities and individuals that have informed, fostered, encouraged, critiqued, challenged, and supported this work.

To Dr. Kristie Briggs and Dr. Anne York, you are both incredible teachers; thank you for instilling in me an appreciation for scholarship, evidence, and rigor. My appreciation of your generosity during my years at Creighton continues to grow.

To my teams of collaborators from my years at Cerner: thank you for showing me what a supportive and collectively interested community of impassioned peers looks like, setting the bar so high, and teaching me when to ask for help. And to my Cerner Research noodlers: Christy, Sarah, Ryan, Harlen, and Kelly. Thank you for encouraging this leap.

To the team at Southcentral Foundation: Steve, Michelle, Doug, Mike, and Melanie. Thank you for welcoming me into your space and your philosophy. Thank you for always reminding me that people are at the center of all of this, and we lose sight of that at our peril. You are the organizational manifestation of empathy, and you inspire me.

To Dr. David McCallie: Thank you for your mentorship, guidance, and steadying hand as I have taken my first few steps into this arena. Your clarity of thought, insight, and indefatigable pragmatism have helped ground me during this program. I return regularly to the numerous words of wisdom you've shared.

To the HPMers and health IT policy crew: Casey, ECAD, Abdulaziz, Kevin, Heather, Robin, Carol, Katy, EG, Joanna, Brittney, A Jay, Jordan, Dori, and Genna. You all are simply the best, and I couldn't have asked for a better family of colleagues and collaborators. The energy, creativity, and raw intelligence in this group is just amazing.

To the Health Policy & Management department: this is a truly special place. Thank you all for your commitment to students and endless well of energy to shape the department and program into its best form. I am also grateful to the National Library of Medicine, which has provided funding for my doctoral studies.

To Chris: I cannot imagine a better advisor and collaborator. Over these four years you have taught me an incalculable amount about how to motivate, formulate, and conduct meaningful research. Your mentorship has fundamentally shaped the way I approach the world and my work, and has taught me invaluable lessons about how to be a generous mentor, leader, and researcher. Thank you for your patience, support, and guidance over the last four years. Thank you for your emphasis on first principles and simplicity, and for calling me out on my circumlocutory and sesquipedalian tendencies.

To my committee members, Josh, Justin, Julia, and Brian: Thank you for your time, expertise, rigor, and standards of excellence to which you have held this work. This dissertation would be a shadow of its current self without your guidance. I am truly indebted to you all for helping me become the researcher I am today.

To Casey, I'm honored and proud to have undertaken this journey with you. You have made me a better researcher, a more systematic critical thinker, and made every day in the office great. I'm sorry for all of the bad puns, half-baked research ideas, and overly detailed stories you got in return.

To Marc, Joe, Cy, Laura, Lauren, Vivek, Roy, Mike, Wil, Joe, Jack, Caitlin, Lauren, Thomas, and others, thank you for the miles, the laughs, the music, the beers, trips, and check-ins, and all of the joy that comes in the hours spent away from a dissertation. I love this work, but I love you all more.

To Dick & Laura Flanigan: Thank you for your warmth, enthusiasm, and support during this journey and all the others over the last 15 years. Thanks for making sure I keep at least one foot on the ground and thank you for the generosity and love you've given to me and my family over the years.

Finally, to my mom, my most ardent and steadfast supporter and invaluable source of unconditional love, baked goods, and much-needed swift kicks. I cannot begin to imagine the magnitude of the sacrifice you have made – and continue to make – to support this endeavor. Thank you for your selflessness and guidance, your good humor and grace. No words I write here can adequately capture how lucky I feel to have had you and dad to shape me into who I am today. Thank you, for everything. I love you.

Nathan Calvert Apathy

HEALTH INFORMATION EXCHANGE USE IN PRIMARY CARE

The United States has invested over $40 billion in digitizing the health care system, yet the anticipated gains in improved care coordination, quality, and cost savings remain largely unrealized. This is due in part to limited interoperability and low rates of health information exchange (HIE) use, which can support care coordination and improve provider decision-making. Primary care providers are central to the US health care delivery system and frequently function as care coordinators, yet capability and HIE use gaps among these providers limit the potential of these digital systems to achieve their intended goals.

I study HIE use in the context of primary care to examine 1) factors associated with provider HIE use, 2) the extent and nature of team-based HIE use, and 3) differences in HIE system use patterns across discrete groups of system users. First, I use a national sample of primary care providers to analyze market and practice factors related to HIE use for patient referrals. Overall, I find that only 43% of primary care provider referrals used HIE. Furthermore, I find substantial variation in HIE use rates across electronic health record (EHR) vendors. Second, I use HIE system log data to understand the breadth and depth of HIE use among teams, a care model underpinning primary care delivery reform efforts. I find that although use of HIE systems remains low, in primary care settings it overwhelmingly takes place in a manner consistent with team-based care workflows. Furthermore, team-based use does not differ in breadth from single provider HIE use, but illustrates less depth before and after visits. Third, I apply cluster analysis to 16 HIE use measures representing 7 use attributes, and identify 5 discrete user groups. I then compare two of these user groups and find user-level variation in volume and efficiency of use, both of which have implications for HIE system design and usability improvements. Ultimately, these findings help to inform how HIE use can be increased and improved in primary care, moving the US health care system closer to realizing the coordination, quality, and cost savings made possible by a digitized delivery system.

Christopher A. Harle, MS, PhD, Co-Chair

Joshua R. Vest, MPH, PhD, Co-Chair

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

21CC	21st Century Cures
ADE	Adverse Drug Event
AHRF	Area Health Resource File
AHRQ	Agency for Healthcare Research & Quality
AJHC	Anthony Jordan Health Center
C-CDA	Consolidated Clinical Document Architecture
CDS	Clinical Decision Support
CLARA	Clustering LARge Applications
COPD	Chronic Obstructive Pulmonary Disorder
CPOE	Computerized Physician Order Entry
ED	Emergency Department
EHR	Electronic Health Record
eHI	eHealth Initiative
eSCR	Electronic Summary of Care
FQHC	Federally Qualified Health Center
FTC	Federal Trade Commission
HAS	Health Service Area
HCC	Hierarchical Condition Category
HHI	Herfindahl-Hirschman Index
HIE	Health Information Exchange
HITECH	Health Information Technology for Economic and Clinical Health Act
HRSA	Health Resources Services Administration

HUD	Housing and Urban Development
IT	Information Technology
MACRA	Medicare Access and CHIP Reauthorization Act
MANOVA	Multiple Analysis of Variance
MIPS	Merit-Based Incentive Program
NCQA	National Committee for Quality Assurance
NPI	National Provider Identifier
ONC	Office of the National Coordinator for Health IT
OOCHC	Oak Orchard Community Health Center
PAM	Partitioning Around Medoids
PCMH	Patient Centered Medical Home
PI	Promoting Interoperability
RHIO	Regional Health Information Organization
RPCN	Rochester Primary Care Network
US	United States
WSS	Weighted Sum of Squares

Chapter 1: Introduction

Background

Over the past 15 years, the United States (US) health care industry has become increasingly digitized. Electronic health records (EHRs) are now nearly ubiquitous in hospitals and present in the vast majority of physician practices [1.1, 1.2]. These high rates of adoption represent considerable growth since President George W. Bush's initial push to digitize patient records in 2004 [1.3, 1.4], when less than a quarter of providers used EHRs [1.5, 1.6]. Much of this growth can be traced to the 2009 Health Information Technology for Clinical and Economic Health (HITECH) Act, which encouraged adoption of EHRs among both hospitals and providers via incentives totaling over $30 billion as of 2018 [1.7–1.9]. More recent policy efforts, including the Medicare Access and CHIP Reauthorization Act of 2015 (MACRA) and the 21st Century Cures Act of 2018 (21CC), have sustained this investment to advance digitization of the US health care system [1.10, 1.11]. Projections of the benefits from broad health information technology (IT) adoption emphasized quality improvements in the domains of efficiency, patient safety, and patient health outcomes via preventive care provision and chronic disease management [1.12]. However, cost-savings projections emphasized that fully realizing many of these benefits depended upon the ability of health IT systems to interoperate and share patient health information across providers and organizations [1.13].

<u>Progress in Health Information Technology Research</u>

As health IT adoption and use has increased, researchers have regularly assessed progress towards these anticipated benefits, returning to interoperability and health information exchange (HIE) as key factors. In the context of this dissertation, health information exchange refers to the act of exchanging patient information between care providers or organizations [1.14]. I differentiate this definition of HIE from the organizational definition, as in an entity that facilitates information exchange between care providers. I refer to these entities as “health information organizations” rather than health information exchanges throughout this dissertation. Interoperability, separate from HIE, refers to the integration of exchanged data into electronic health record systems and other clinical databases. Importantly, interoperability requires no special effort on the part of the care provider to obtain or integrate data [1.14].

A 2006 systematic review by Chaudhry et al. identified key quality improvements from health IT in the areas of improved guideline adherence in particular for preventive services, decreased medication errors, and decreased utilization [1.15]. These early studies were concentrated among early adopters of health IT; organizations that represent a cadre of hospitals and provider organizations demonstrating benefits that may reflect high baseline quality and successful implementations [1.16]. With respect to health information exchange, the authors noted that only one percent of studies at the time had focused on health IT systems with the capability to connect to outside systems, an “area critical to the capacity for health information technology to fundamentally change health care” [1.15].

In 2009, Goldzweig, et al. updated this review with further support for the effectiveness of health IT in improving preventive services delivery and mixed effects of health IT on chronic disease management [1.16]. This study also observed an increase in studies from later-adopting organizations and those evaluating vendor-based rather than homegrown EHR systems, an important step in evaluating if and to what extent findings from early adopters are generalizable [1.16]. While the authors did not focus explicitly on interoperability or health information exchange studies, they did reiterate that the projected cost savings of health IT systems required vastly greater levels of interoperability than existed at the time. To support this goal, the authors suggested policymakers ease the financial burden of health IT adoption for hospitals and providers. In response, alleviating some of this financial burden was one aspect of the HITECH Act's EHR Incentive Program ("Meaningful Use," now termed "Promoting Interoperability" as of 2018).

The final review of pre-HITECH studies by Buntin, et al. further supported generally positive effects of health IT implementations, particularly in the areas of efficiency and effectiveness [1.17]. This study also observed a continuation of the trend of later-adopting organizations publishing more studies that largely aligned with findings from early adopters, a good sign for generalizability of the gains from health IT adoption. Despite this rapidly growing body of literature on health IT generally, the authors highlighted only one study examining HIE and utilization, which found equivocal results and tempered expectations of HIE's potential to reduce overall utilization [1.18]. Furthermore, follow-up studies of the facilitators and barriers to the success of the HITECH Act's provisions [1.19] noted the lack of widespread interoperable HIE and its importance to the success of the policy:

> Key goals of HITECH - including enhanced patient care, improved clinical outcomes and population health, and increased system efficiency - cannot be met unless information is not only digitized through well-formulated electronic health records but also exchanged in a timely way across the health delivery system and with patients and the public.
> (Gold, 2012)

After the passage of the HITECH Act, with its multi-billion dollar investment in health IT adoption and provisions to encourage and enable more exchange of health information [1.7, 1.19, 1.20], it was imperative to re-assess the health IT literature with a lens tailored to this new regulatory environment. To this end, Jones, et al. documented the increasing rate of growth in health IT evaluation research and examined the outcomes of quality, safety, and efficiency across health IT functions incentivized in the HITECH Act, including HIE [1.21]. The authors found clinical decision support (CDS) and computerized physician order entry (CPOE) to be the two most commonly evaluated functions, especially with respect to their relationship with quality outcomes. The broader quality domain - including process, satisfaction, and patient health outcomes - illustrated overwhelmingly positive findings, primarily in the areas of chronic care management and preventive service delivery, consistent with previous reviews [1.16, 1.17]. In the safety domain, 78% of medication-related studies reported positive results, spanning care environments and numerous outcomes. Efficiency outcomes, specifically utilization, demonstrated mixed findings in terms of the effects of health IT on rates of care utilization. This is due in part to the fact that care utilization can increase or decrease appropriately, depending on the health IT functionality or intervention under evaluation. For example, in one study found that visits for treatment among patients with HIV increased after implementing HIE for test results, a positive change despite higher utilization [1.22]. When taking this into consideration, 85% of the studies reported an “appropriate” change in utilization. Provider and patient time use - another important efficiency outcome - was equivocal in its conclusions. While studies reliably illustrated decreases in length of stay, reductions in turn-around time for diagnostic testing, and quicker initiation of therapies [1.23, 1.24], providers reported that health IT systems had increased documentation burden and crowded out meaningful face-to-face time with the patient [1.25–1.27].

Jones, et al. noted 33 studies examining HIE between 2007 and 2013, a marked increase from the Buntin, et al. study finding only one [1.17, 1.21]. These studies illustrated predominantly positive results in the domains of utilization, cost, and patient health outcomes. Most focused on laboratory results exchange capabilities, showing moderately decreased rates of laboratory test ordering, especially for new patients when results were available electronically [1.24, 1.28, 1.29]. Other work identified improved health outcomes and preventive services for HIV patients [1.22] and faster identification of appropriate treatment [1.24]. One HIE evaluation study in a hospital setting noted decreased emergency and primary care visits, but increased utilization of specialist visits [1.30]. The Jones, et al. review represents considerable progress in HIE research, yet these studies examined a rather narrow set of HIE use cases relative to those laid out in early cost savings projections [1.13]. Furthermore, benefits from HIE may accrue due to any number of underlying mechanisms (e.g. more complete information, system maturity, etc.). However, only one of these studies analyzed a mechanism - in this case, time - underlying HIE's effect on lab test ordering [1.29]. This gap was consistent across the studies identified by Jones, et al. As a result, the authors concluded that, given the proliferation of generally encouraging evidence of health IT's effects, researchers should focus future efforts to understand the more precise mechanisms underlying health IT's relationship to these outcomes [1.21]. Recent studies have heeded this call, pushing forward the evidence base on precisely how health IT systems can be designed, implemented, and used to best achieve quality, efficiency, and safety outcomes while avoiding clinician burnout [1.31–1.39].

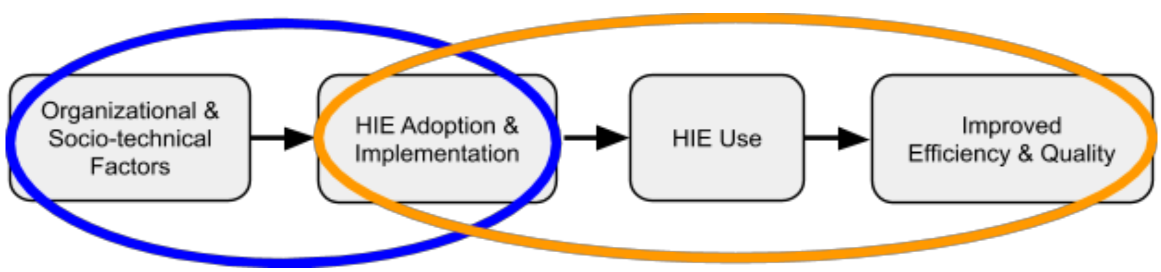
Health Information Exchange

Taken together, the collective studies of health IT noted above highlight that while important gains have been made - in particular in the domains of preventive care delivery, disease management, and medication safety - fully leveraging health IT towards its purported benefits will require growth in adoption and use of interoperable HIE, which has lagged overall health IT adoption. To an extent, this lag is unavoidable as the underlying digital infrastructure of EHRs and information networks is a necessary precursor to functional HIE [1.40]. However, given that nearly all hospitals have adopted EHRs [1.1], we might expect more progress in HIE adoption than has been observed in national surveys of HIE capabilities [1.41–1.43].

In 2017, 88% of hospitals reported the ability to send information electronically, and 74% reported the ability to receive data [1.42]. These are encouraging rates for two important HIE capabilities, but only 53% of hospitals reported the ability to integrate data from outside sources [1.42], a more advanced capability pivotal to achieving many of health IT's potential benefits [1.44]. Physician practices, which traditionally lag hospitals in health IT adoption, show the same pattern with HIE capabilities. In 2017, 53% of physicians reported the ability to query for patient information; this was the most widely reported HIE capability among physicians [1.43]. Only 28% reported the ability to integrate information from outside sources, close to half the rate of hospitals [1.43]. The lag in HIE adoption has in turn delayed the realization of system-wide benefits including more complete information at the point of care, better-informed care decisions, improved care quality, increased efficiency, and reduced costs of care [1.13, 1.20, 1.45, 1.46]. While normative levels of HIE adoption are unclear, it is generally understood that to achieve these benefits, hospitals and physician practices must increase their adoption and use of HIE going forward [1.44, 1.47].

Due in part to this lag in adoption and use of HIE, research in the HIE stream of health IT literature has proceeded down two paths (Figure 1.1). First, in an effort to understand how to bolster HIE adoption and use, scholars have examined the barriers and facilitators to HIE adoption and use. This is captured in the blue circle in Figure 1.1. Second, researchers have continued the evaluative work summarized above, investigating the effects of HIE adoption and use on quality of care (care coordination, patient safety, patient outcomes, etc.) and efficiency (testing utilization, cost, etc.). This is represented by the orange circle in Figure 1.1 below. I first summarize the "barriers and facilitators" literature, then summarize the recent "effects" literature. There are, of course, additional streams of HIE-related research, including large bodies of work regarding public health use cases [1.48–1.58], HIE and provider market dynamics [1.59–1.66], and informatics approaches to implementing HIE systems, among others.

Figure 1.1 Sub-streams of HIE Literature Summarized



Facilitators and Barriers to HIE Adoption and Use

A number of recent systematic reviews have summarized key barriers and facilitators to organizational HIE adoption and clinical HIE use [1.67–1.71]. Adoption of HIE among hospitals and office-based physicians has been hindered historically by legal and regulatory complexity [1.72], implementation costs [1.73–1.75], concerns around losing competitive advantage [1.76], and a lack of solid evidence supporting the benefits of HIE use [1.75,1.77]. Furthermore, implementation in these settings has faced hurdles related to workflow integration [1.78], incomplete data within the HIE [1.79], security and privacy concerns [1.80], and a lack of standards to enable interoperability [1.81]. As HIE is used in less than 10 percent of encounters, on average [1.69], studies of barriers to HIE use have reiterated some of these challenges like incomplete data [1.82,1.83], but has emphasized a lack of usability and workflow integration [1.84–1.86]. To facilitate HIE adoption and use, literature supports the effectiveness of financial incentives [1.72,1.87], socio-technical considerations during implementation [1.88], robust and ongoing user training [1.82,1.89,1.90], and consideration of opt-out instead of opt-in policies for patient consent to share data [1.83,1.85,1.91,1.92]. Taken together, these barriers and facilitators highlight the importance of regulatory attention, to ensure continued adoption and use of HIE.

Because HIE is generally undertaken as a local effort, a series of surveys administered between 2008 and 2015 based on the eHealth Initiative (eHI) survey of HIE organizations have tracked progress in, barriers to, and facilitators of local and regional HIE efforts over time [1.93–1.97]. The most recent survey of HIE efforts was not encouraging, illustrating a decline in HIE efforts nationwide and raising concerns about the long-term future of interoperable HIE in the US [1.97]. This finding called further attention to policymakers to understand and alleviate the remaining barriers, especially in the regulatory arena. These barriers derive in part from regulatory complexity impacting both hospitals and organizations facilitating information exchange [1.98,1.99]. In particular, while progress has been made in some regulatory areas like "information blocking," organizations continue to have difficulty navigating complex webs of privacy and consent laws that often vary across state lines [1.99]. These laws govern how patients can provide consent for providers to share their information with other providers via health information exchange. Evidence has thus far illustrated that defined consent policies paired with incentives have demonstrated a positive relationship with regional HIE efforts [1.100] and hospital participation in those efforts [1.101], but more work is needed to understand the relationships between varying regulatory approaches and the success (or failure) of local and regional HIE efforts.

Effects and Outcomes of HIE Adoption and Use

Despite the challenges to adoption and use noted above, HIE efforts using modern HIE systems have been underway for over a decade in the US. Researchers have focused on these settings to identify the effects of HIE adoption and use and to gauge whether or not the purported benefits of HIE are realized in practice. Here again, several literature reviews have focused on synthesizing this evidence [1.69,1.102–1.105], finding mixed evidence and somewhat methodologically weak studies until more recent years. Some of the strongest evidence of HIE's effects has been in the study of duplicative testing, with a panoply of studies showing a modest but significant relationship between HIE use and reduced laboratory and radiology tests [1.106–1.108]. Extending these findings to calculate cost savings has also illustrated modest savings deriving from HIE use, primarily in emergency department (ED) settings [1.109,1.110]. In other utilization domains, there is considerable evidence for reductions in readmissions and avoidable admissions to the hospital [1.111–1.118]. Importantly, these findings are concentrated in hospital and emergency department settings, and a recent study examining post-acute transitions to long-term care settings found no effect of HIE use on readmissions [1.119].

The evidence of HIE's effects on patient health outcomes is less robust [1.103,1.104]. HIE use has illustrated a positive effect on mammography screening rates and various measures of ambulatory quality, including other recommended preventive screenings [1.120,1.121]. More detailed clinical measures of health have also been studied, with Proeschold-Bell, et al. showing rigorously that HIE use improved clinical measures of health status for HIV-positive individuals [1.122]. This finding is congruent with additional work illustrating improved HIV clinical outcomes with HIE-enabled alerts [1.123]. Boockvar, et al used a randomized design to examine medication-related outcomes, but found no effect of HIE use on adverse drug events (ADEs) [1.124]. Finally, one study has found a positive effect of HIE adoption on in-hospital mortality, studying hospital transfers from five states over three years [1.125]. In summary, the literature examining HIE's impact on patient health outcomes is still relatively nascent, compared to utilization and cost research. This is due in part to the difficulty of measuring HIE use [1.126], which often involves HIE system log files [1.44,1.127]. This measurement challenge has warranted its own study as the field has progressed and led to calls for more theoretically-informed, consistent, and granular measures of HIE system use [1.44,1.127].

The Challenge of Measuring HIE Use

Notably, two literature reviews have specifically highlighted that studies of HIE use tend to vary in the ways they measure "system use" [1.69,1.127]. The most popular measure of HIE use is a binary indicator of HIE access, typically measured at the visit level using data from the HIE log files or from the EHR [1.109,1.116,1.120,1.128–1.135]. Studies have also used availability of HIE post implementation as an independent variable in pre/post analyses [1.28,1.30,1.136] and randomized studies that compare groups exposed to the availability of HIE [1.110,1.122,1.124,1.137]. Still others use hospital or practice-level reported adoption of HIE derived from organizational surveys like the American Hospital Association (AHA) Information Technology supplement [1.29,1.106,1.125,1.138–1.140]. More granular measures of HIE use in this stream have mostly come from studies outside the US, primarily Israel [1.111,1.118,1.133,1.141–1.146]. Given this variation in measurement, there has been some work to characterize and describe HIE use. These studies have either developed typologies of HIE use [1.86,1.145] or identified patient and provider characteristics associated with different types of HIE use [1.147–1.149].

Common Settings of HIE Research

Finally, while the broader health IT evaluation literature including EHRs, CPOE, and other functions has historically been well-balanced across ambulatory providers and hospitals [1.16,1.21], the same cannot be said for HIE research [1.105]. There exists a considerable body of evidence regarding HIE adoption and use among hospitals and emergency departments, but very few recent HIE studies have taken place in primary care settings [1.105,1.150]. As noted by Cross, et al., in order to fully understand the effects of HIE, study of diverse care settings and transitions is needed [1.119].

To address this gap, I situate this dissertation in the context of primary care. Chapter 2 expands knowledge regarding practice and market factors that are related to the amount of primary care provider HIE use. Chapter 3 investigates if and to what extent HIE tools support primary care delivery reform efforts, in particular team-based care workflows. Furthermore, we seek to understand if team-based use of HIE tools differs in its nature from provider use. Finally, chapter 4 aims to identify discrete groups of HIE system users among a group of primary care users, to inform HIE system design that extends beyond "one-size-fits-all" workflows and addresses user preferences with dynamic workflows informed by observed system use.

My work informs efforts to increase provider use of HIE and federal regulatory approaches to HIE, tests the feasibility of proposed HIE quality measures, provides the first explicit measurement of team-based HIE use, measures the extent to which HIE supports primary care delivery reform, applies and extends a conceptual framework of multidimensional HIE use [1.144], identifies discrete groups of HIE users that cross-cut clinical team roles, and offers recommendations for HIE system interface customization based on those groups. Taken together, my dissertation contributes to both the "barriers and facilitators" and "HIE use" literature streams described above. Below I describe for each of my three studies the specific literature gap I address, the study objective, and each study's contribution to health information technology literature.

Practice and Market Factors Associated with HIE Use

In chapter 2 of my dissertation, I address a gap in the "barriers and facilitators" literature in understanding the practice and market-level factors that are related to primary care provider HIE use volume. As noted above, provider adoption and use of HIE has historically lagged that of hospitals, making it imperative to understand the factors related to HIE use among providers [1.43,1.151]. Despite this, we know relatively little regarding the factors influencing HIE adoption and use in primary care settings [1.104,1.105], even though over 480 million primary care provider visits occur each year [1.152]. Furthermore, there exists no evidence regarding the factors related to the *volume* of HIE use among primary care providers. While qualitative research has unearthed many barriers, the factors facilitating increased HIE use for primary care providers remain unknown. Success of HIE efforts depends not only on adoption but widespread use; this study aims to analyze the factors at the practice and market level that relate to higher or lower levels of HIE use among providers. Knowledge of these factors can inform state and federal approaches to increase HIE use among primary care physicians and other office-based providers.

The objective of this first study is to identify the factors associated with provider HIE use volume. I examine this question in a nationwide sample of primary care providers, cardiologists, and orthopedic surgeons in Medicare. Specifically, this study explores if and to what extent practice and market factors such as size, EHR vendor, system membership, beneficiary mix, market concentration, regional socioeconomic factors, and state HIE consent policy (opt-in or opt-out) are associated with varying provider levels of HIE use. It also compares primary care providers to a sample of cardiologists and surgeons, to identify heterogeneity in these relationships across provider specialties. I measure HIE use as the percentage of patient referrals sent with an electronic summary of care (eSCR), a required regulatory measure for Meaningful Use Stage 2 (now "Promoting Interoperability") and measure of HIE use volume.

This study contributes to the "barriers and facilitators" literature by expanding our understanding of the mechanisms that may facilitate or impede primary care provider use of HIE. Furthermore, I contribute to the HIE use measurement literature by conducting the first study using data from provider-level MU Stage 2 attestation to operationalize an important construct of HIE use, namely the volume of HIE use. Other studies have used this measure to examine volume of HIE among hospitals [1.92,1.153,1.154]; to my knowledge, this is the first study measuring volume of HIE among providers. Finally, I contribute to the HIE literature in general by expanding our understanding of how HIE varies across different settings. As most HIE studies are set in acute care settings or emergency departments, primary care is an under-studied setting in the broader HIE literature [1.105], despite its status as a cornerstone of care coordination in the US health care ecosystem [1.155,1.156].

Team-Based Use of HIE in Primary Care

In chapter 3, I address the HIE use measurement literature as well as the primary care delivery reform literature. HIE use measurement has thus far lacked measures of HIE use that go beyond individual clinical HIE users and individual patient visits [1.127]. As noted above, measures of HIE use tend to be binary indicators of "any use," with the most granular measures operationalizing use patterns for individual users. Team-based measures of HIE use suggested by national advisory bodies and a literature review of HIE measurement approaches [1.127,1.157] have yet to be implemented. These measures are particularly relevant in modern primary care settings, especially those implementing delivery reform efforts like the Patient-Centered Medical Home (PCMH) that depend on robust information technology and HIE in particular to support team-based care delivery workflows and whole-person care [1.158]. Despite its relevance to primary care delivery reform, the extent to which HIE use in primary care supports team-based care models remains unknown. Furthermore, it remains to be seen whether or not team-based HIE use results in broader or deeper use, thereby increasing the information available to care team relative to single-user HIE use.

The objective of this second study is two-fold. First, I quantify the extent of team-based use of HIE in primary care settings. Second, I aim to understand if and to what extent team-based use of HIE is related to broader or deeper use of these systems, compared to single-user, non-team-based use. I use granular measures of HIE breadth and depth derived from system use logs from a regional HIE in New York state to construct team-based use measures, limiting the study to HIE use from three PCMHs to identify primary care settings engaging in delivery reform efforts.

Primarily, this study advances the knowledge of HIE in support of primary care delivery reform efforts, specifically the PCMH initiative emphasizing team-based care models. Robust HIE is fundamental to the success of these innovative models of care, and my study examines the degree to which existing HIE tools are being used in support of these efforts in primary care. I also contribute to literature regarding measurement of HIE use, by establishing replicable measures of team use that enable future studies of team HIE use. This is innovative in that these measures can be used to further our understanding of the distinct benefits and outcomes from specific types of HIE use. Furthermore, this study contributes to the development of quality measures of usability, availability of exchanged information, and other aspects of health IT use that are byproducts of the care process and thus bestow less onerous reporting requirements on health care provider organizations [1.44,1.159].

User-Level Patterns of HIE Use

Finally, in chapter 4, I address a second gap in the HIE use measurement literature which thus far lacks an evidence base pertaining to user-level patterns of HIE system use [1.127]. These patterns can be utilized to inform the design of dynamic user interfaces that adapt to user needs based on historical use patterns and improve upon the one-size-fits-all approach of most HIE systems [1.86,1.144]. While several studies have characterized and categorized session-level HIE system use across dimensions such as diversity, intensity, granularity, and duration [1.80,1.119,1.135,1.142,1.144,1.148, 1.160], I am aware of no studies characterizing use patterns at the user level. This gap leads to a lack of knowledge with respect to discrete categories of HIE system users that may cut across user roles. Furthermore, measuring use at the user level can help to quantify rates of under-use and system rejection, as well as tease apart more "average" users from superusers and non-users, all of which may have varying needs and preferences from the HIE system.

The objective of my third study is to measure and classify HIE users according to HIE use measures across the attributes of participation, volume, duration, granularity, diversity, content, and efficiency. I apply and extend a conceptual framework of multidimensional HIE use to inform my use measures [1.144]. Using the same HIE log data from chapter 3, I conduct a cluster analysis to identify discrete user groups demonstrating different use patterns. Secondarily, I examine the ways in which user groups vary in their aggregate measures of use, and analyze the ways in which non-outlier user groups differ from one another in terms of the relationships between measures of HIE use. My findings are pertinent to HIE system designers and implementers seeking to understand how different types of users behave and how these systems can be modified to improve user experience and increase system utility.

This study contributes to the HIE measurement literature by applying and extending a validated measurement framework to the study of user-level HIE use. I extend the existing framework via the attributes of efficiency and participation, in order to quantify the barriers to accessing clinical information and user-level participation in HIE system use. Future researchers can leverage these attributes and measures in studies examining the precise nature of HIE use and its impact on clinical decision-making and care quality outcomes. This study also contributes to the systemization of HIE measurement studies, which frequently suffer from lack of external validity and inconsistent measurement operationalization [1.69,1.104,1.127]. Finally, this study offers evidence to system designers pertaining to user profiles that may improve user experience and improve the efficiency of HIE system use.

References

1.1 Office of the National Coordinator for Health Information Technology. Non-federal Acute Care Hospital Electronic Health Record Adoption. Office of the National Coordinator for Health Information Technology 2017. dashboard.healthit.gov/quickstats/pages/FIG-Hospital-EHR-Adoption.php

1.2 Office of the National Coordinator for Health IT. Office-Based Physician Health IT Adoption and Use. Health IT Dashboard | Data. 2019.https://dashboard.healthit.gov/datadashboard/documentation/physician-health-it-adoption-use-data-documentation.php (accessed 2 Oct 2019).

1.3 Transforming Health Care: The President's Health Information Technology Plan. The White House: President George W. Bush. 2006.https://georgewbush-whitehouse.archives.gov/infocus/technology/economic_policy200404/chap3.html (accessed 7 Nov 2019).

1.4 Allen M. Bush touts plan for electronic medicine. Washington Post 2004;28.

1.5 Fonkych K, Taylor R. The State and Pattern of Health Information Technology Adoption. Rand Corporation 2005. https://play.google.com/store/books/details?id=hzjcvryvI5wC

1.6 Bates DW. Physicians and ambulatory electronic health records. Health Aff 2005;24:1180–9. doi:10.1377/hlthaff.24.5.1180

1.7 Blumenthal D. Launching HITECH. N Engl J Med 2010;362:382–5. doi:10.1056/NEJMp0912825

1.8 Adler-Milstein J, Jha AK. HITECH Act Drove Large Gains In Hospital Electronic Health Record Adoption. Health Aff Published Online First: 5 September 2017.http://www.healthaffairs.org/doi/10.1377/hlthaff.2016.1651 (accessed 9 Nov 2017).

1.9 Data & Reports. Centers for Medicare and Medicaid Services Promoting Interoperability Programs. 2019.https://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/DataAndReports.html (accessed 12 Nov 2019).

1.10 Centers for Medicare & Medicaid Services (CMS), HHS. Medicare Program; Merit-Based Incentive Payment System (MIPS) and Alternative Payment Model (APM) Incentive Under the Physician Fee Schedule, and Criteria for Physician-Focused Payment Models. Final rule with comment period. Fed Regist 2016;81:77008–831.https://www.ncbi.nlm.nih.gov/pubmed/27905815

1.11 21st Century Cures Act: Interoperability, Information Blocking, and the ONC Health IT Certification Program. Federal Register 2019. https://www.govinfo.gov/content/pkg/FR-2019-03-04/pdf/2019-02224.pdf

1.12 Hillestad R, Bigelow J, Bower A, et al. Can electronic medical record systems transform health care? Potential health benefits, savings, and costs. Health Aff 2005;24:1103–17. doi:10.1377/hlthaff.24.5.1103

1.13 Walker J, Pan E, Johnston D, et al. The value of health care information exchange and interoperability. Health Aff 2005;Suppl Web Exclusives:W5–10 – W5–18. doi:10.1377/hlthaff.w5.10

1.14 Dixon BE. Chapter 1 - What is Health Information Exchange? In: Dixon BE, ed. Health Information Exchange. Academic Press 2016. 3–20. doi:10.1016/B978-0-12-803135-3.00001-3
1.15 Chaudhry B, Wang J, Wu S, et al. Systematic review: impact of health information technology on quality, efficiency, and costs of medical care. Ann Intern Med 2006;144:742–52. doi:10.7326/0003-4819-144-10-200605160-00125
1.16 Goldzweig CL, Towfigh A, Maglione M, et al. Costs And Benefits Of Health Information Technology: New Trends From The Literature. Health Aff 2009;28:w282–93. doi:10.1377/hlthaff.28.2.w282
1.17 Buntin MB, Burke MF, Hoaglin MC, et al. The benefits of health information technology: a review of the recent literature shows predominantly positive results. Health Aff 2011;30:464–71. doi:10.1377/hlthaff.2011.0178
1.18 Vest JR. Health information exchange and healthcare utilization. J Med Syst 2009;33:223–31.https://www.ncbi.nlm.nih.gov/pubmed/19408456
1.19 Gold MR, McLaughlin CG, Devers KJ, et al. Obtaining providers'‘buy-in'and establishing effective means of information exchange will be critical to HITECH's success. Health Aff 2012;31:514–26.https://www.healthaffairs.org/doi/abs/10.1377/hlthaff.2011.0753
1.20 Williams C, Mostashari F, Mertz K, et al. From the Office of the National Coordinator: the strategy for advancing the exchange of health information. Health Aff 2012;31:527–36. doi:10.1377/hlthaff.2011.1314
1.21 Jones SS, Rudin RS, Perry T, et al. Health information technology: an updated systematic review with a focus on meaningful use. Ann Intern Med 2014;160:48–54. doi:10.7326/M13-1531
1.22 Virga PH, Jin B, Thomas J, et al. Electronic health information technology as a tool for improving quality of care and health outcomes for HIV/AIDS patients. Int J Med Inform 2012;81:e39–45. doi:10.1016/j.ijmedinf.2012.06.006
1.23 Georgiou A, Prgomet M, Paoloni R, et al. The Effect of Computerized Provider Order Entry Systems on Clinical Care and Work Processes in Emergency Departments: A Systematic Review of the Quantitative Literature. Ann Emerg Med 2013;61:644–53.e16. doi:10.1016/j.annemergmed.2013.01.028
1.24 Bell DS, Cima L, Seiden DS, et al. Effects of laboratory data exchange in the care of patients with HIV. Int J Med Inform 2012;81:e74–82. doi:10.1016/j.ijmedinf.2012.07.012
1.25 Duffy RL, Yiu SSA, Molokhia E, et al. Effects of electronic prescribing on the clinical practice of a family medicine residency. Fam Med 2010;42:358–63.https://www.ncbi.nlm.nih.gov/pubmed/20455110
1.26 Munyisia EN, Yu P, Hailey D. Does the introduction of an electronic nursing documentation system in a nursing home reduce time on documentation for the nursing staff? Int J Med Inform 2011;80:782–92. doi:10.1016/j.ijmedinf.2011.08.009
1.27 Tang JW, Kushner RF, Cameron KA, et al. Electronic tools to assist with identification and counseling for overweight patients: a randomized controlled trial. J Gen Intern Med 2012;27:933–9. doi:10.1007/s11606-012-2022-8

1.28 Hebel E, Middleton B, Shubina M, et al. Bridging the chasm: effect of health information exchange on volume of laboratory testing. Arch Intern Med 2012;172:517–9. doi:10.1001/archinternmed.2011.2104
1.29 Ross SE, Radcliff TA, Leblanc WG, et al. Effects of health information exchange adoption on ambulatory testing rates. J Am Med Inform Assoc 2013;20:1137–42. doi:10.1136/amiajnl-2012-001608
1.30 Mäenpää T, Asikainen P, Gissler M, et al. Outcomes assessment of the regional health information exchange: a five-year follow-up study. Methods Inf Med 2011;50:308–18. doi:10.3414/ME10-01-0048
1.31 Holmgren AJ, Co Z, Newmark L, et al. Assessing the safety of electronic health records: a national longitudinal study of medication-related decision support. BMJ Qual Saf Published Online First: 18 July 2019. doi:10.1136/bmjqs-2019-009609
1.32 Barnett ML, Mehrotra A, Jena AB. Adverse inpatient outcomes during the transition to a new electronic health record system: observational study. BMJ 2016;354:i3835. doi:10.1136/bmj.i3835
1.33 Lin SC, Jha AK, Adler-Milstein J. Electronic Health Records Associated With Lower Hospital Mortality After Systems Have Time To Mature. Health Aff 2018;37:1128–35. doi:10.1377/hlthaff.2017.1658
1.34 Adler-Milstein J, Nong P. Early experiences with patient generated health data: health system and patient perspectives. J Am Med Inform Assoc Published Online First: 22 April 2019. doi:10.1093/jamia/ocz045
1.35 McCullough JS, Parente ST, Town R. Health information technology and patient outcomes: the role of information and labor coordination. Rand J Econ 2016;47:207–36. doi:10.1111/1756-2171.12124
1.36 Pendergrass JC, Chandrasekaran R. Key Factors Affecting Ambulatory Care Providers' Electronic Exchange of Health Information With Affiliated and Unaffiliated Partners: Web-Based Survey Study. JMIR Med Inform 2019;7:e12000. doi:10.2196/12000
1.37 Shanafelt TD, Dyrbye LN, Sinsky C, et al. Relationship Between Clerical Burden and Characteristics of the Electronic Environment With Physician Burnout and Professional Satisfaction. Mayo Clin Proc 2016;91:836–48. doi:10.1016/j.mayocp.2016.05.007
1.38 Gardner RL, Cooper E, Haskell J, et al. Physician stress and burnout: the impact of health information technology. J Am Med Inform Assoc 2019;26:106–14. doi:10.1093/jamia/ocy145
1.39 Melnick ER, Dyrbye LN, Sinsky CA, et al. The Association Between Perceived Electronic Health Record Usability and Professional Burnout Among US Physicians. Mayo Clin Proc Published Online First: 14 November 2019. doi:10.1016/j.mayocp.2019.09.024
1.40 Adler-Milstein J, Everson J, Lee S-YD. Sequencing of EHR adoption among US hospitals and the impact of meaningful use. J Am Med Inform Assoc 2014;21:984–91. doi:10.1136/amiajnl-2014-002708
1.41 Holmgren AJ, Patel V, Adler-Milstein J. Progress In Interoperability: Measuring US Hospitals' Engagement In Sharing Patient Data. Health Aff 2017;36:1820–7. doi:10.1377/hlthaff.2017.0546

1.42 Pylypchuk Y, Johnson C, Henry J, et al. Variation in Interoperability among U.S. Non-federal Acute Care Hospitals in 2017. Office of the National Coordinator on Health IT 2018. https://www.healthit.gov/sites/default/files/page/2018-11/Interop%20variation_0.pdf
1.43 Patel V, Pylypchuk Y, Parasrampuria S, et al. Interoperability among Office-Based Physicians in 2015 and 2017. Office of the National Coordinator for Health IT 2019. https://www.healthit.gov/sites/default/files/page/2019-05/ONC-Data-Brief-47-Interoperability-among-Office-Based-Physicians-in-2015-and-2017.pdf
1.44 Bates DW, Samal L. Interoperability: What Is It, How Can We Make It Work for Clinicians, and How Should We Measure It in the Future? Health Serv Res 2018;53:3270–7. doi:10.1111/1475-6773.12852
1.45 Adjerid I, Adler-Milstein J, Angst C. Reducing Medicare Spending Through Electronic Health Information Exchange: The Role of Incentives and Exchange Maturity. Information Systems Research 2018;29:341–61. doi:10.1287/isre.2017.0745
1.46 Vest JR, Gamm LD. Health information exchange: persistent challenges and new strategies. J Am Med Inform Assoc 2010;17:288–94. doi:10.1136/jamia.2010.003673
1.47 Walker DM. Does participation in health information exchange improve hospital efficiency? Health Care Manag Sci 2018;21:426–38. doi:10.1007/s10729-017-9396-4
1.48 Shapiro JS, Mostashari F, Hripcsak G, et al. Using health information exchange to improve public health. Am J Public Health 2011;101:616–23. doi:10.2105/AJPH.2008.158980
1.49 Dixon BE, Gamache RE, Grannis SJ. Towards public health decision support: a systematic review of bidirectional communication approaches. J Am Med Inform Assoc 2013;20:577–83. doi:10.1136/amiajnl-2012-001514
1.50 Goldwater J, Jardim J, Khan T, et al. Emphasizing Public Health Within a Health Information Exchange: An Evaluation of the District of Columbia's Health Information Exchange Program. EGEMS (Wash DC) 2014;2:1090. doi:10.13063/2327-9214.1090
1.51 Dixon BE, Vreeman DJ, Grannis SJ. The long road to semantic interoperability in support of public health: experiences from two states. J Biomed Inform 2014;49:3–8. doi:10.1016/j.jbi.2014.03.011
1.52 van Panhuis WG, Paul P, Emerson C, et al. A systematic review of barriers to data sharing in public health. BMC Public Health 2014;14:1144. doi:10.1186/1471-2458-14-1144
1.53 Hersh WR, Totten AM, Eden KB, et al. Outcomes From Health Information Exchange: Systematic Review and Future Research Needs. JMIR Med Inform 2015;3:e39. doi:10.2196/medinform.5215
1.54 Shah GH, Vest JR, Lovelace K, et al. Local Health Departments' Partners and Challenges in Electronic Exchange of Health Information. J Public Health Manag Pract 2016;22 Suppl 6, Public Health Informatics:S44–50. doi:10.1097/PHH.0000000000000442
1.55 Shah GH, Leider JP, Luo H, et al. Interoperability of Information Systems Managed and Used by the Local Health Departments. J Public Health Manag Pract

2016;22 Suppl 6, Public Health Informatics:S34–43. doi:10.1097/PHH.0000000000000436
1.56 Gibson PJ, Shah GH, Streichert LC, et al. Urgent Challenges for Local Public Health Informatics. J Public Health Manag Pract 2016;22 Suppl 6, Public Health Informatics:S6–8. doi:10.1097/PHH.0000000000000479
1.57 Rajamani S, Kayser A, Emerson E, et al. Evaluation of Data Exchange Process for Interoperability and Impact on Electronic Laboratory Reporting Quality to a State Public Health Agency. Online Journal of Public Health Informatics 2018;10.http://www.firstmonday.dk/ojs/index.php/ojphi/article/viewFile/9317/7584
1.58 Matney SA, Heale B, Hasley S, et al. Lessons Learned in Creating Interoperable Fast Healthcare Interoperability Resources Profiles for Large-Scale Public Health Programs. Appl Clin Inform 2019;10:87–95. doi:10.1055/s-0038-1677527
1.59 Adler-Milstein J, Jha AK. Health information exchange among U.S. hospitals: who’s in, who's out, and why? Healthc (Amst) 2014;2:26–32. doi:10.1016/j.hjdsi.2013.12.005
1.60 Everson J, Adler-Milstein J. Engagement In Hospital Health Information Exchange Is Associated With Vendor Marketplace Dominance. Health Aff 2016;35:1286–93. doi:10.1377/hlthaff.2015.1215
1.61 Vest JR, Menachemi N. A population ecology perspective on the functioning and future of health information organizations. Health Care Manage Rev Published Online First: 1 November 2017. doi:10.1097/HMR.0000000000000185
1.62 Everson J, Adler-Milstein J. Gaps in health information exchange between hospitals that treat many shared patients. J Am Med Inform Assoc 2018;25:1114–21. doi:10.1093/jamia/ocy089
1.63 Vest JR, Simon K. Hospitals’ adoption of intra-system information exchange is negatively associated with inter-system information exchange. J Am Med Inform Assoc Published Online First: 30 May 2018. doi:10.1093/jamia/ocy058
1.64 Martinez DA, Feijoo F, Zayas-Castro JL, et al. A strategic gaming model for health information exchange markets. Health Care Manag Sci 2018;21:119–30. doi:10.1007/s10729-016-9382-2
1.65 Lin SC, Adler-Milstein J. The relationship between hospital and ehr vendor market dynamics on health information organization presence and participation. BMC Med Inform Decis Mak 2018;18:28. doi:10.1186/s12911-018-0605-y
1.66 Everson J, Adler-Milstein J. Sharing information electronically with other hospitals is associated with increased sharing of patients. Health Serv Res 2019;36:223. doi:10.1111/1475-6773.13240
1.67 Edwards A, Hollin I, Barry J, et al. Barriers to cross--institutional health information exchange: a literature review. J Healthc Inf Manag 2010;24:22–34.https://www.ncbi.nlm.nih.gov/pubmed/20677469
1.68 Kruse CS, Regier V, Rheinboldt KT. Barriers over time to full implementation of health information exchange in the United States. JMIR Med Inform 2014;2:e26. doi:10.2196/medinform.3625
1.69 Rudin RS, Motala A, Goldzweig CL, et al. Usage and effect of health information exchange: a systematic review. Ann Intern Med 2014;161:803–11. doi:10.7326/M14-0877

1.70 Wu H, Larue E. Barriers and Facilitators of Health Information Exchange (HIE) Adoption in the United States. 2015 48th Hawaii International Conference on System Sciences. 2015. doi:10.1109/hicss.2015.356
1.71 Eden KB, Totten AM, Kassakian SZ, et al. Barriers and facilitators to exchanging health information: a systematic review. Int J Med Inform 2016;88:44–51. doi:10.1016/j.ijmedinf.2016.01.004
1.72 Anderson JG. Social, ethical and legal barriers to e-health. Int J Med Inform 2007;76:480–3. doi:10.1016/j.ijmedinf.2006.09.016
1.73 Fontaine P, Zink T, Boyle RG, et al. Health information exchange: participation by Minnesota primary care practices. Arch Intern Med 2010;170:622–9. doi:10.1001/archinternmed.2010.54
1.74 Ross SE, Schilling LM, Fernald DH, et al. Health information exchange in small-to-medium sized family medicine practices: motivators, barriers, and potential facilitators of adoption. Int J Med Inform 2010;79:123–9. doi:10.1016/j.ijmedinf.2009.12.001
1.75 Vest JR, Campion TR Jr, Kaushal R, et al. Challenges, alternatives, and paths to sustainability for health information exchange efforts. J Med Syst 2013;37:9987. doi:10.1007/s10916-013-9987-7
1.76 Vest JR. More than just a question of technology: factors related to hospitals' adoption and implementation of health information exchange. Int J Med Inform 2010;79:797–806. doi:10.1016/j.ijmedinf.2010.09.003
1.77 Hincapie A, Warholak T. The Impact of Health Information Exchange on Health Outcomes. Appl Clin Inform 2011;02:499–507. doi:10.4338/ACI-2011-05-R-0027
1.78 Unertl KM, Johnson KB, Gadd CS, et al. Bridging organizational divides in health care: an ecological view of health information exchange. JMIR Med Inform 2013;1:e3. doi:10.2196/medinform.2510
1.79 Dixon BE, Jones JF, Grannis SJ. Infection preventionists' awareness of and engagement in health information exchange to improve public health surveillance. Am J Infect Control 2013;41:787–92. doi:10.1016/j.ajic.2012.10.022
1.80 Vest JR, Jasperson 'jon Sean. How are health professionals using health information exchange systems? Measuring usage for evaluation and system improvement. J Med Syst 2012;36:3195–204. doi:10.1007/s10916-011-9810-2
1.81 Miller AR, Tucker C. Health information exchange, system size and information silos. J Health Econ 2014;33:28–42. doi:10.1016/j.jhealeco.2013.10.004
1.82 Rudin R, Volk L, Simon S, et al. What Affects Clinicians' Usage of Health Information Exchange? Appl Clin Inform 2011;2:250–62. doi:10.4338/ACI-2011-03-RA-0021
1.83 Yeager VA, Walker D, Cole E, et al. Factors related to health information exchange participation and use. J Med Syst 2014;38:78. doi:10.1007/s10916-014-0078-1
1.84 Thorn SA, Carter MA, Bailey JE. Emergency physicians' perspectives on their use of health information exchange. Ann Emerg Med 2014;63:329–37. doi:10.1016/j.annemergmed.2013.09.024
1.85 Kierkegaard P, Kaushal R, Vest JR. How could health information exchange better meet the needs of care practitioners? Appl Clin Inform 2014;5:861–77. doi:10.4338/ACI-2014-06-RA-0055

1.86 Unertl KM, Johnson KB, Lorenzi NM. Health information exchange technology on the front lines of healthcare: workflow factors and patterns of use. J Am Med Inform Assoc 2012;19:392–400. doi:10.1136/amiajnl-2011-000432
1.87 Patel V, Abramson EL, Edwards A, et al. Physicians' potential use and preferences related to health information exchange. Int J Med Inform 2011;80:171–80. doi:10.1016/j.ijmedinf.2010.11.008
1.88 Ozkaynak M, Brennan PF. Revisiting sociotechnical systems in a case of unreported use of health information exchange system in three hospital emergency departments. J Eval Clin Pract 2013;19:370–3. doi:10.1111/j.1365-2753.2012.01837.x
1.89 Finnell JT, Overhage JM. Emergency medical services: the frontier in health information exchange. AMIA Annu Symp Proc 2010;2010:222–6.https://www.ncbi.nlm.nih.gov/pubmed/21346973
1.90 Gadd CS, Ho Y-X, Cala CM, et al. User perspectives on the usability of a regional health information exchange. J Am Med Inform Assoc 2011;18:711–6. doi:10.1136/amiajnl-2011-000281
1.91 Bouhaddou O, Bennett J, Cromwell T, et al. The Department of Veterans Affairs, Department of Defense, and Kaiser Permanente Nationwide Health Information Network exchange in San Diego: patient selection, consent, and identity matching. AMIA Annu Symp Proc 2011;2011:135–43.https://www.ncbi.nlm.nih.gov/pubmed/22195064
1.92 Apathy NC, Holmgren AJ. Opt-in consent policies: potential barriers to hospital health information exchange. Am J Manag Care 2020.
1.93 Adler-Milstein J, McAfee AP, Bates DW, et al. The State Of Regional Health Information Organizations: Current Activities And Financing. Health Aff 2008;27:w60–9. doi:10.1377/hlthaff.27.1.w60
1.94 Adler-Milstein J, Bates DW, Jha AK. U.S. Regional health information organizations: progress and challenges. Health Aff 2009;28:483–92. doi:10.1377/hlthaff.28.2.483
1.95 Adler-Milstein J, Bates DW, Jha AK. A survey of health information exchange organizations in the United States: implications for meaningful use. Ann Intern Med 2011;154:666–71. doi:10.7326/0003-4819-154-10-201105170-00006
1.96 Adler-Milstein J, Bates DW, Jha AK. Operational Health Information Exchanges Show Substantial Growth, But Long-Term Funding Remains A Concern. Health Aff 2013;32:1486–92. doi:10.1377/hlthaff.2013.0124
1.97 Adler-Milstein J, Lin SC, Jha AK. The Number Of Health Information Exchange Efforts Is Declining, Leaving The Viability Of Broad Clinical Data Exchange Uncertain. Health Aff 2016;35:1278–85. doi:10.1377/hlthaff.2015.1439
1.98 Schmit CD, Wetter SA, Kash BA. Falling short: how state laws can address health information exchange barriers and enablers. J Am Med Inform Assoc 2018;25:635–44. doi:10.1093/jamia/ocx122
1.99 Mello MM, Adler-Milstein J, Ding KL, et al. Legal Barriers to the Growth of Health Information Exchange-Boulders or Pebbles? Milbank Q 2018;96:110–43. doi:10.1111/1468-0009.12313

1.100 Adjerid I, Acquisti A, Telang R, et al. The Impact of Privacy Regulation and Technology Incentives: The Case of Health Information Exchanges. Manage Sci 2016;62:1042–63. doi:10.1287/mnsc.2015.2194
1.101 Brown-Podgorski BL, Hilts KE, Kash BA, et al. The Association Between State-Level Health Information Exchange Laws and Hospital Participation in Community Health Information Organizations. AMIA Annu Symp Proc 2018;2018:313–20.https://www.ncbi.nlm.nih.gov/pubmed/30815070
1.102 Rahurkar S, Vest JR, Menachemi N. Despite The Spread Of Health Information Exchange, There Is Little Evidence Of Its Impact On Cost, Use, And Quality Of Care. Health Aff Published Online First: March 2015.https://www.healthaffairs.org/doi/abs/10.1377/hlthaff.2014.0729 (accessed 25 Feb 2018).
1.103 Hersh WR, Totten AM, Eden K, et al. The Evidence Base for Health Information Exchange. In: Health Information Exchange. Elsevier 2016. 213–29.
1.104 Menachemi N, Rahurkar S, Harle CA, et al. The benefits of health information exchange: an updated systematic review. J Am Med Inform Assoc Published Online First: 28 April 2018. doi:10.1093/jamia/ocy035
1.105 Dobrow MJ, Bytautas JP, Tharmalingam S, et al. Interoperable Electronic Health Records and Health Information Exchanges: Systematic Review. JMIR Med Inform 2019;7:e12607. doi:10.2196/12607
1.106 Lammers EJ, Adler-Milstein J, Kocher KE. Does health information exchange reduce redundant imaging? Evidence from emergency departments. Med Care 2014;52:227–34. doi:10.1097/MLR.0000000000000067
1.107 Carr CM, Gilman CS, Krywko DM, et al. Observational study and estimate of cost savings from use of a health information exchange in an academic emergency department. J Emerg Med 2014;46:250–6. doi:10.1016/j.jemermed.2013.05.068
1.108 Winden TJ, Boland LL, Frey NG, et al. Care everywhere, a point-to-point HIE tool: utilization and impact on patient care in the ED. Appl Clin Inform 2014;5:388–401. doi:10.4338/ACI-2013-12-RA-0100
1.109 Frisse ME, Johnson KB, Nian H, et al. The financial impact of health information exchange on emergency department care. J Am Med Inform Assoc 2012;19:328–33. doi:10.1136/amiajnl-2011-000394
1.110 Yaraghi N. An empirical analysis of the financial benefits of health information exchange in emergency departments. J Am Med Inform Assoc 2015;22:1169–72. doi:10.1093/jamia/ocv068
1.111 Ben-Assuli O, Shabtai I, Leshno M. The impact of EHR and HIE on reducing avoidable admissions: controlling main differential diagnoses. BMC Med Inform Decis Mak 2013;13:49. doi:10.1186/1472-6947-13-49
1.112 Vest JR, Unruh MA, Freedman S, et al. Health systems' use of enterprise health information exchange vs single electronic health record vendor environments and unplanned readmissions. J Am Med Inform Assoc Published Online First: 26 July 2019. doi:10.1093/jamia/ocz116
1.113 Unruh MA, Jung H-Y, Kaushal R, et al. Hospitalization event notifications and reductions in readmissions of Medicare fee-for-service beneficiaries in the Bronx, New York. J Am Med Inform Assoc 2017;24:e150–6. doi:10.1093/jamia/ocw139

1.114 Kash BA, Baek J, Davis E, et al. Review of successful hospital readmission reduction strategies and the role of health information exchange. Int J Med Inform 2017;104:97–104. doi:10.1016/j.ijmedinf.2017.05.012
1.115 Jones SS, Friedberg MW, Schneider EC. Health information exchange, Health Information Technology use, and hospital readmission rates. AMIA Annu Symp Proc 2011;2011:644–53.https://www.ncbi.nlm.nih.gov/pubmed/22195120
1.116 Vest JR, Kern LM, Silver MD, et al. The potential for community-based health information exchange systems to reduce hospital readmissions. J Am Med Inform Assoc 2015;22:435–42. doi:10.1136/amiajnl-2014-002760
1.117 Vest JR, Unruh MA, Shapiro JS, et al. The associations between query-based and directed health information exchange with potentially avoidable use of health care services. Health Serv Res Published Online First: 21 May 2019. doi:10.1111/1475-6773.13169
1.118 Ben-Assuli O, Shabtai I, Leshno M. Using electronic health record systems to optimize admission decisions: the Creatinine case study. Health Informatics J 2015;21:73–88. doi:10.1177/1460458213503646
1.119 Cross DA, McCullough JS, Banaszak-Holl J, et al. Health information exchange between hospital and skilled nursing facilities not associated with lower readmissions. Health Serv Res Published Online First: 10 October 2019. doi:10.1111/1475-6773.13210
1.120 Kern LM, Barrón Y, Dhopeshwarkar RV, et al. Health information exchange and ambulatory quality of care. Appl Clin Inform 2012;3:197–209. doi:10.4338/ACI-2012-02-RA-0005
1.121 Pitts SI, Maruthur NM, Wang X, et al. Team-Based Health Information Exchange Use Increased Mammography Documentation and Referral in an Academic Primary Care Practice: An Interrupted Time Series. J Gen Intern Med 2018;33:710–4. doi:10.1007/s11606-017-4259-8
1.122 Proeschold-Bell RJ, Belden CM, Parnell H, et al. A randomized controlled trial of health information exchange between human immunodeficiency virus institutions. J Public Health Manag Pract 2010;16:521–8. doi:10.1097/PHH.0b013e3181df78b9
1.123 Magnus M, Herwehe J, Gruber D, et al. Improved HIV-related outcomes associated with implementation of a novel public health information exchange. Int J Med Inform 2012;81:e30–8. doi:10.1016/j.ijmedinf.2012.06.005
1.124 Boockvar KS, Ho W, Pruskowski J, et al. Effect of health information exchange on recognition of medication discrepancies is interrupted when data charges are introduced: results of a cluster-randomized controlled trial. J Am Med Inform Assoc 2017;24:1095–101. doi:10.1093/jamia/ocx044
1.125 Usher M, Sahni N, Herrigel D, et al. Diagnostic Discordance, Health Information Exchange, and Inter-Hospital Transfer Outcomes: a Population Study. J Gen Intern Med 2018;33:1447–53. doi:10.1007/s11606-018-4491-x
1.126 Yeager VA, Vest JR, Walker DM, et al. Challenges to Conducting Health Information Exchange Research and Evaluation: Reflections and Recommendations for Examining the Value of HIE. eGEMs 2017;5:15. doi:10.5334/egems.217

1.127 Vest JR, Jasperson J. What should we measure? Conceptualizing usage in health information exchange. J Am Med Inform Assoc 2010;17:302–7. doi:10.1136/jamia.2009.000471
1.128 Bailey JE, Pope RA, Elliott EC, et al. Health information exchange reduces repeated diagnostic imaging for back pain. Ann Emerg Med 2013;62:16–24. doi:10.1016/j.annemergmed.2013.01.006
1.129 Everson J, Kocher KE, Adler-Milstein J. Health information exchange associated with improved emergency department care through faster accessing of patient information from outside organizations. J Am Med Inform Assoc 2017;24:e103–10. doi:10.1093/jamia/ocw116
1.130 Vest JR, Kern LM, Campion TR Jr, et al. Association between use of a health information exchange system and hospital admissions. Appl Clin Inform 2014;5:219–31. doi:10.4338/ACI-2013-10-RA-0083
1.131 Jung H-Y, Vest JR, Unruh MA, et al. Use of Health Information Exchange and Repeat Imaging Costs. J Am Coll Radiol 2015;12:1364–70. doi:10.1016/j.jacr.2015.09.010
1.132 Bailey JE, Wan JY, Mabry LM, et al. Does health information exchange reduce unnecessary neuroimaging and improve quality of headache care in the emergency department? J Gen Intern Med 2013;28:176–83. doi:10.1007/s11606-012-2092-7
1.133 Park H, Lee S-I, Hwang H, et al. Can a health information exchange save healthcare costs? Evidence from a pilot program in South Korea. Int J Med Inform 2015;84:658–66. doi:10.1016/j.ijmedinf.2015.05.008
1.134 Vest JR, Kaushal R, Silver MD, et al. Health information exchange and the frequency of repeat medical imaging. Am J Manag Care 2014;20:eSP16–24.https://www.ncbi.nlm.nih.gov/pubmed/25811815
1.135 Vest JR, Gamm LD, Ohsfeldt RL, et al. Factors associated with health information exchange system usage in a safety-net ambulatory care clinic setting. J Med Syst 2012;36:2455–61. doi:10.1007/s10916-011-9712-3
1.136 Wilcox AB, Shen S, Dorr DA, et al. Improving access to longitudinal patient health information within an emergency department. Appl Clin Inform 2012;3:290–300. doi:10.4338/ACI-2011-03-RA-0019
1.137 Lang E, Afilalo M, Vandal AC, et al. Impact of an electronic link between the emergency department and family physicians: a randomized controlled trial. CMAJ 2006;174:313–8. doi:10.1503/cmaj.050698
1.138 Chen M, Guo S, Tan X. Does Health Information Exchange Improve Patient Outcomes? Empirical Evidence From Florida Hospitals. Health Aff 2019;38:197–204. doi:10.1377/hlthaff.2018.05447
1.139 Eftekhari S, Yaraghi N, Singh R, et al. Do Health Information Exchanges Deter Repetition of Medical Services? ACM Trans Manage Inf Syst 2017;8:2:1–2:27. doi:10.1145/3057272
1.140 Ayabakan S. The Impact of Health Information Sharing on Duplicate Testing. Management Information Systems Quarterly 2017;41:1083–103.
1.141 Ben-Assuli O, Shabtai I, Leshno M, et al. EHR in emergency rooms: exploring the effect of key information components on main complaints. J Med Syst 2014;38:36. doi:10.1007/s10916-014-0036-y

1.142 Nirel N, Rosen B, Sharon A, et al. The impact of an integrated hospital-community medical information system on quality and service utilization in hospital departments. Int J Med Inform 2010;79:649–57. doi:10.1016/j.ijmedinf.2010.06.005
1.143 Vest JR, Grinspan ZM, Kern LM, et al. Using a health information exchange system for imaging information: patterns and predictors. AMIA Annu Symp Proc 2013;2013:1402–11.https://www.ncbi.nlm.nih.gov/pubmed/24551416
1.144 Politi L, Codish S, Sagy I, et al. Use patterns of health information exchange through a multidimensional lens: conceptual framework and empirical validation. J Biomed Inform 2014;52:212–21. doi:10.1016/j.jbi.2014.07.003
1.145 Politi L, Codish S, Sagy I, et al. Balancing volume and duration of information consumption by physicians: The case of health information exchange in critical care. J Biomed Inform 2017;71:1–15. doi:10.1016/j.jbi.2017.05.007
1.146 Politi L, Codish S, Sagy I, et al. Use patterns of health information exchange systems and admission decisions: Reductionistic and configurational approaches. Int J Med Inform 2015;84:1029–38. doi:10.1016/j.ijmedinf.2015.06.012
1.147 Vest JR, Jasperson 'jon Sean, Zhao H, et al. Use of a health information exchange system in the emergency care of children. BMC Med Inform Decis Mak 2011;11:78. doi:10.1186/1472-6947-11-78
1.148 Vest JR, Zhao H, Jasperson J, et al. Factors motivating and affecting health information exchange usage. J Am Med Inform Assoc 2011;18:143–9. doi:10.1136/jamia.2010.004812
1.149 Johnson KB, Unertl KM, Chen Q, et al. Health information exchange usage in emergency departments and clinics: the who, what, and why. J Am Med Inform Assoc 2011;18:690–7. doi:10.1136/amiajnl-2011-000308
1.150 Fontaine P, Ross SE, Zink T, et al. Systematic review of health information exchange in primary care practices. J Am Board Fam Med 2010;23:655–70. doi:10.3122/jabfm.2010.05.090192
1.151 Pylypchuk Y, Alvarado CS, Patel V, et al. Uncovering differences in interoperability across hospital size. Healthc (Amst) Published Online First: 16 April 2019. doi:10.1016/j.hjdsi.2019.04.001
1.152 Ambulatory Care Use and Physician office visits. CDC: National Center for Health Statistics FastStats. 2019.https://www.cdc.gov/nchs/fastats/physician-visits.htm (accessed 21 Nov 2019).
1.153 Lin SC, Everson J, Adler-Milstein J. Technology, Incentives, or Both? Factors Related to Level of Hospital Health Information Exchange. Health Serv Res Published Online First: 28 February 2018. doi:10.1111/1475-6773.12838
1.154 Lin SC, Hollingsworth JM, Adler-Milstein J. Alternative payment models and hospital engagement in health information exchange. Am J Manag Care 2019;25:e1–6.https://www.ncbi.nlm.nih.gov/pubmed/30667611
1.155 Rothman AA, Wagner EH. Chronic illness management: what is the role of primary care? Ann Intern Med 2003;138:256–61. doi:10.7326/0003-4819-138-3-200302040-00034
1.156 Doty MM, Tikkanen R, Shah A, et al. Primary Care Physicians' Role In Coordinating Medical And Health-Related Social Needs In Eleven Countries. Health Aff 2020;39:115–23. doi:10.1377/hlthaff.2019.01088

1.157 National Quality Forum. A Measurement Framework to Assess Nationwide Progress Related to Interoperable Health Information Exchange to Support the National Quality Strategy. Office of the National Coordinator for Health IT 2017. https://www.qualityforum.org/Projects/i-m/Interoperability_2016-2017/Final_Report.aspx
1.158 Adler-Milstein J, Cohen GR. Implementing the IT infrastructure for health reform: adoption of health IT among patient-centered medical home practices. AMIA Annu Symp Proc 2013;2013:11–6.https://www.ncbi.nlm.nih.gov/pubmed/24551318
1.159 Adler-Milstein J, Embi PJ, Middleton B, et al. Crossing the health IT chasm: considerations and policy recommendations to overcome current challenges and enable value-based care. J Am Med Inform Assoc 2017;24:1036–43. doi:10.1093/jamia/ocx017
1.160 Li X, Xue Y, Malin B. Towards Understanding the Usage Pattern of Web-based Electronic Medical Record Systems. World Wirel Mob Multimed Netw 2011;2011. doi:10.1109/WoWMoM.2011.5986195

Chapter 2: Practice and Market Factors Associated with HIE Use

Introduction

Reducing care fragmentation in US health care depends upon the exchange of information between providers for effective care coordination and cost savings [2.1–2.3]. This health information exchange (HIE) relies upon a robust infrastructure of health information technology (IT) to connect providers and hospitals [2.4,2.5]. This infrastructure has grown following the 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act, as nearly all hospitals have adopted electronic health records (EHRs) and EHRs are present in 85% of office-based practices. [2.6,2.7]. The HITECH Act also implemented requirements within the Meaningful Use (MU, now "Promoting Interoperability") incentive program for eligible hospitals and providers to establish the necessary connectivity to enable HIE, however HIE capabilities remain stubbornly behind other health IT capabilities like computerized physician order entry (CPOE), especially among office-based providers [2.8]. In 2017, only 36% of office-based providers reported sending any electronic data to outside providers, despite high rates of EHR adoption [2.8]. Furthermore, we know little about the nature of the HIE taking place among office-based providers [2.9,2.10]. Specifically, the volume of HIE that is occurring among providers with HIE capabilities remains unknown.

Beginning in Stage 2 of the MU program, eligible providers were required to report the proportion of patient referrals sent with electronic summary of care (eSCR) documents. eSCR documents contain 16 elements of structured patient data including demographic information, visit information, and clinical information about the patient such as the problem list, current medications, allergies, and laboratory results, among other data [2.11]. While methods to send analog summary of care documents are well-established (e.g. fax), providers face a number of hurdles to sending eSCRs with referrals. Primarily, the receiving provider must have the capability to receive eSCRs from the sending provider, which involves either direct methods like an EHR interface or methods that use a mediator like a community health information exchange organization.

Beyond the technical capability hurdles, practice characteristics may be correlated with the volume of HIE in which a provider engages. For example, providers in an integrated health system with a shared EHR experience few barriers to HIE for within-system referrals. On the other hand, if a provider is in a small independent practice, the expense of establishing connections to each provider to whom the practice refers may present a high cost and thus limit HIE to referrals only with "connected" providers. Furthermore, practices with more complex patients may make more referrals which in turn may justify the costs of establishing and using HIE with providers with whom the practice regularly shares patients. Finally, EHR vendors have been shown to vary with respect to performance on a number of MU measures [2.12], and have been accused of engaging in "information blocking" behaviors that may in turn reduce the volume of HIE.

The broader health care market in which providers compete may also impact the volume of HIE. For example, in more competitive markets, providers may perceive a disincentive to share patient information, as it may erode market share. Also, having a higher quantity of EHR-equipped providers to whom a provider could refer may serve to increase HIE volume. Additionally, state-level variation in consent policies for sharing of patient health data has been cited as a key challenge for the growth of HIE. Specifically, opt-in policies that require the provider to consent each patient to sharing information with other providers may introduce administrative costs that depress HIE volume [2.13].

We hypothesize provider HIE volume to be related to several practice- and market-level factors. First, we hypothesize that HIE volume will be greater among providers who are system-affiliated, as they are likely to experience fewer technical hurdles and have greater availability of providers to whom they may refer. For similar reasons, we expect HIE volume to be greater among providers in larger practices. Second, we hypothesize that providers who see more complex patients, on average, will demonstrate greater volume of HIE. Third, we hypothesize that the provider's EHR vendor is unrelated to HIE volume, as all certified EHR systems are required to have the capability to send eSCRs and thus should not independently be related to HIE volume. Among market factors, we hypothesize that providers in areas with few exchange partners will demonstrate lower HIE volume. We also hypothesize that providers in more competitive markets will demonstrate lower HIE volume, on average. Finally, we expect HIE volume to be negatively associated with opt-in state consent policies. While the literature has explored provider-level adoption of HIE capabilities [2.8,2.14], the extent to which these practice and market forces relate to the volume of HIE among HIE-adopting providers remains unknown.

To address this gap, we analyzed national provider-level data from Stage 2 of the MU program in 2016, the first year in which eligible providers were required to report the volume of HIE, measured as the percentage of referrals sent with eSCRs. In our primary analysis, we combine this data with provider, practice, and market characteristics to understand if and to what extent provider volume of HIE is associated with these factors.

Our findings directly inform ongoing efforts to increase the level of HIE in the US health care system towards the ends of reducing care fragmentation and improving the information available to providers at the point of care. Policy-makers, health systems, and provider practices can use these findings to understand the factors that may increase HIE nationwide or within specific markets.

Methods

Data & Sample

We combined public data from seven sources for analyses. First, our primary outcome variable, provider volume of HIE use, came from MU Stage 2 Public Use Files published by the Centers for Medicare and Medicaid Services (CMS). These data include the reported values submitted to CMS for each required MU measure for all eligible providers, identified by National Provider Identifier (NPI). As reported by CMS, MU performance measures are not linked to specific practices; rather we retrieved practice affiliations from our second data source, the Physician Compare National Downloadable File for December 2016. This provided physician and practice-level characteristics, linked by NPI to the MU data. Third, we used data published by the Office of the National Coordinator for Health Information Technology (ONC) that captures the specific software used for MU attestation for each provider, program stage, and program year. Fourth, we used the 2016 Medicare Fee-For-Service Provider Utilization & Payment Data Physician and Other Supplier Public Use File [2.15] to capture provider-level standardized Part B payments for the year. This standardization consists of adjusting providers' Part B payment totals for regional variation in costs to enable comparisons across geographies. This data also included average beneficiary age, average beneficiary Hierarchical Condition Category (HCC) risk score, and the proportion of a providers' Part B beneficiary population with specific chronic diseases. Fifth, state-level consent policy data was drawn from a recent study of state laws impacting HIE as of 2016 [2.16]. Sixth, we used the Agency for Healthcare Research and Quality (AHRQ) 2016 Compendium of US Health Systems to identify practices affiliated with larger health systems [2.17]. Finally, county-level control variables were drawn from the 2016 Area Health Resource File made available by the Health Resources and Services Administration (HRSA).

To compare providers with similar practices, we limited the sample of providers to those with primary specialties of primary care, cardiology, and orthopedic surgery consistent with prior literature seeking to represent the clinical domains of primary care, medical subspecialties, and surgery [2.18]. Because providers within these broad domains refer patients to different types of outside providers and settings for different reasons, we focused our analysis on HIE volume, practice factors, and market factors within each of these representative specialties, rather than across specialties.

Outcome: Provider Volume of HIE Use

Our outcome variable was percent of patient referrals sent with eSCR. This was measured as a percentage between 10 and 100. To successfully attest to MU, a provider had to report at least ten percent of referrals sent with eSCR, censoring the data at 10%. Given the modifications that have taken place to MU, our data for analysis was limited only to providers attesting to modified Stage 2 in 2016, so that all providers in the sample were under the same reporting requirements for the same year. Providers received an exclusion from this measure in 2016 if they performed fewer than 100 patient referrals during the 90-day MU reporting period.

Practice Factors

We included nine practice-level factors in our analyses. To capture practice size, we used the number of group members listed in PhysicianCompare. We categorized these values into five groups: solo practice, 2-5 providers, 6-10 providers, 11-50 providers, and more than 50, based on practice size definitions used in work studying provider quality program outcomes [2.19]. EHR vendor for MU attestation came from the EHR Products Used for MU Attestation file published by ONC [2.20]. We linked the MU data via EHR Certification ID, an identifier of the specific software the eligible provider used to attest to MU2 in that year. The eight most common EHR vendors represented 72% of providers in this dataset, and were preserved. All other vendors were categorized as "other" and constituted the reference group for analyses. We identified practices that were system members by matching practice ID from PhysicianCompare to the AHRQ Health System Compendium file, and created a binary indicator for practices that were linked to a health system. To measure prevalence of chronic disease, we included three variables measuring the percentage of beneficiaries the provider saw in 2016 with chronic kidney disease (CKD), diabetes, and hypertension. Finally, we included the average beneficiary age and HCC score to measure overall patient complexity at the provider level. Both disease prevalence and risk score variables are classified here as practice factors, however the measures themselves are at the individual provider level, because different providers at the same practice can vary in the populations they treat. Given that our outcome variable is measured at the individual provider level, we sought to preserve provider-level measures when possible.

Market Factors

To measure market concentration, we combined the Physician Compare data with Part B payments data [2.15] linked to provider NPI to construct a Herfindahl-Hirschman Index (HHI) at the Health Service Area level (HSA). To calculate this measure, individual primary care providers were linked to HSAs via ZIP code per definitions from the department of Housing and Urban Development (HUD) [2.21]. Market share for each provider was calculated as the proportion of the provider's standardized 2016 Medicare payments divided by the total 2016 Medicare payments for all providers within that HSA. The HHI was then calculated for each HSA as the sum of squared market shares within the HSA. Per Federal Trade Commission (FTC) guidelines, we classified each HSA into three groups based on the calculated HHI: not concentrated, moderately concentrated, and highly concentrated [2.22]. The number of available providers for exchange in the HSA was calculated as the number of unique providers reporting in Physician Compare that they used an EHR. Geographic market factors at the county level were included from AHRF 2016-2017 and matched based on provider ZIP code from Physician Compare [2.23]. We included an indicator for Health Professional Shortage Area (no shortage, whole county, or part of the county), the number of Medicare certified hospitals, median household income, percent of persons in poverty, and an indicator for metropolitan and non-metropolitan counties as defined by HRSA. Finally, we included the state HIE consent policy in place in 2016, from a database of state laws impacting HIE [2.16]. Consent policies were coded as opt-in, opt-out, other, or none. States coded as "other" were those with ambiguous laws or laws that describe patient consent to HIE as "voluntary" with no dictated consent scheme [2.24].

Analyses

First, we categorized providers by increments of 10% of transfers sent with eSCR (0%-10%, 11%-20%, etc.), and calculated the number and proportion of providers in each category, to quantify the distribution of HIE volume. To analyze the relationship between HIE volume and the practice and market factors noted above, we used multivariate OLS regression with errors clustered at the practice level. We analyzed primary care providers, cardiologists, and orthopedic surgeons in three separate models, all of which controlled for two provider-level characteristics in analyses: years in practice as a proxy for experience and gender. The final model takes the following form (a full model specification can be found in the Regression Model Details in the appendix):

$$\text{HIEVolume} = \alpha + \beta_1\text{PracticeFactors} + \beta_2\text{MarketFactors} + \beta_3\text{Controls} + \varepsilon$$

We weighted our analyses for providers practicing at multiple locations. Providers practicing in multiple locations were required to aggregate their scores over multiple practices and report only one value to MU, further limiting our ability to observe outcomes at the practice level for all providers affiliated with a practice. Because we did not have organization-specific MU scores in the data but did have providers who appeared more than once, we weighted these observations accordingly. Provider observations were weighted by the inverse of the number of practices they were affiliated with. For example, a provider reporting an affiliation with two practices would receive a weighting of 0.5 for each observation.

Robustness of Model Estimates

As a robustness test for selection into reporting the eSCR measure to MU Stage 2 in 2016, we used a Heckman sample selection model. Because providers who obtain exemptions for the Stage 2 eSCR MU measure may differ systematically from those who are not exempt (e.g. in level of technological sophistication), our linear regression estimates may be both inconsistent and biased because we only observe the outcome variable for providers who did not obtain exemptions [2.25]. Therefore, to adjust the estimates from our main model for potential sample selection effects, we included in the first stage of the Heckman model an identification variable indicating provider exemption (Yes or No) from the HIE volume measure in the prior attestation year, 2015. This was derived from MU Stage 1 or MU Stage 2, depending on the stage to which the provider attested in 2015. A provider could apply for and receive an exemption in both years and in both stages if he or she referred fewer than 100 patients during the 90-day MU reporting period. Therefore, this variable served as a strong - but not perfect - predictor of exemption from this measure in 2016 and as a result was a strong predictor of selection into our analytic sample. Furthermore, to meet the exclusion restriction for the Heckman two-stage model, the identification variable must be unrelated to the outcome, in our case the percentage of referrals sent with eSCR. As exemption is based on patient referral volume during providers' reporting period, it is unlikely to be correlated with the specific proportion of referrals the provider sent with eSCR, as this measure accounts for differences in patient volume across providers. Data preparation and analyses were conducted in R using the RStudio development environment and STATA version 15.1 [2.26–2.28].

Results

The final analytic sample included 26,095 providers attesting to MU Stage 2 in 2016. The vast majority were primary care providers (85.9%, n=22,407), with 2,193 cardiologists and 1,495 orthopedic surgeons. Overall, the average volume of HIE was 45.1% of referrals sent with eSCR (sd=28.1 percentage points). Primary care providers had the lowest HIE volume, on average (42.7%, sd=27.1), while cardiologists had the highest (63.5%, sd=30.9). On average, orthopedic surgeons sent referrals with eSCR in 54.1% of cases (sd=27.8). In bivariate analysis, HIE volume varied significantly across our three provider subgroups ($p<0.001$). A complete table of descriptive statistics of our sample with bivariate analyses can be found in Appendix A, Table A1, and multivariate regression results comparing the three provider subgroups are presented in Appendix A, Table A2. Providers were not distributed evenly across HIE volume groupings (Figure 2.1, below). The most frequently observed HIE volume for primary care providers was between 11 and 20%; 26% (n=5,556) of the primary care providers in our sample reported their HIE volume as just above and including the threshold value of 10%. However, for both cardiologists and orthopedic surgeons, the most common range was between 90 and 100% of referrals sent with eSCR, with 30.7% of cardiologists (n=447) and 15.3% of orthopedic surgeons (n=219) in this highest range. In regression analyses, practice factors were more likely to be associated with HIE volume than market factors (Table 2.1). Below, we report results for each of the sets of factors across the three provider subgroups.

Figure 2.1 Eligible provider performance on Meaningful Use Stage 2: HIE Volume

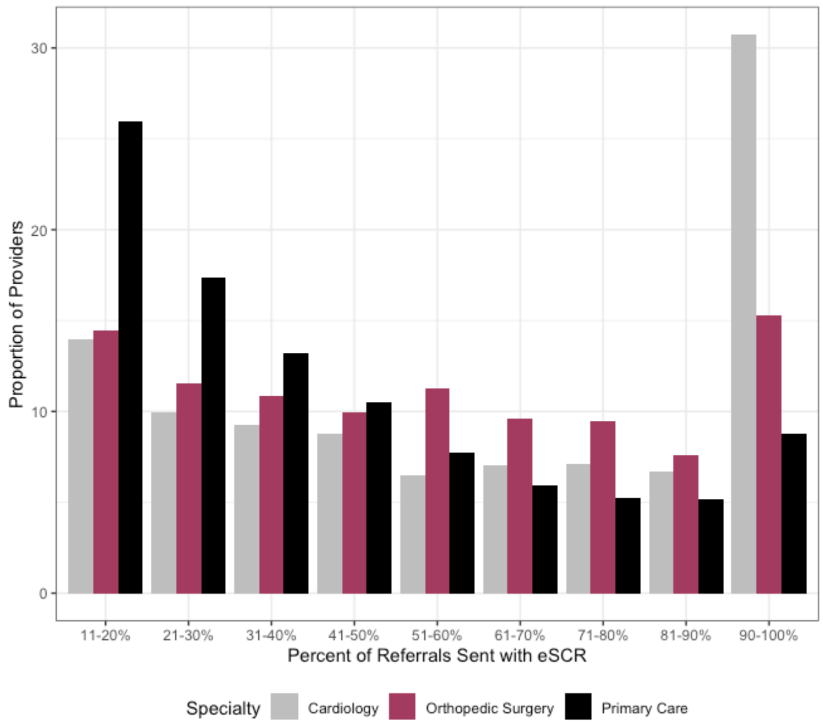
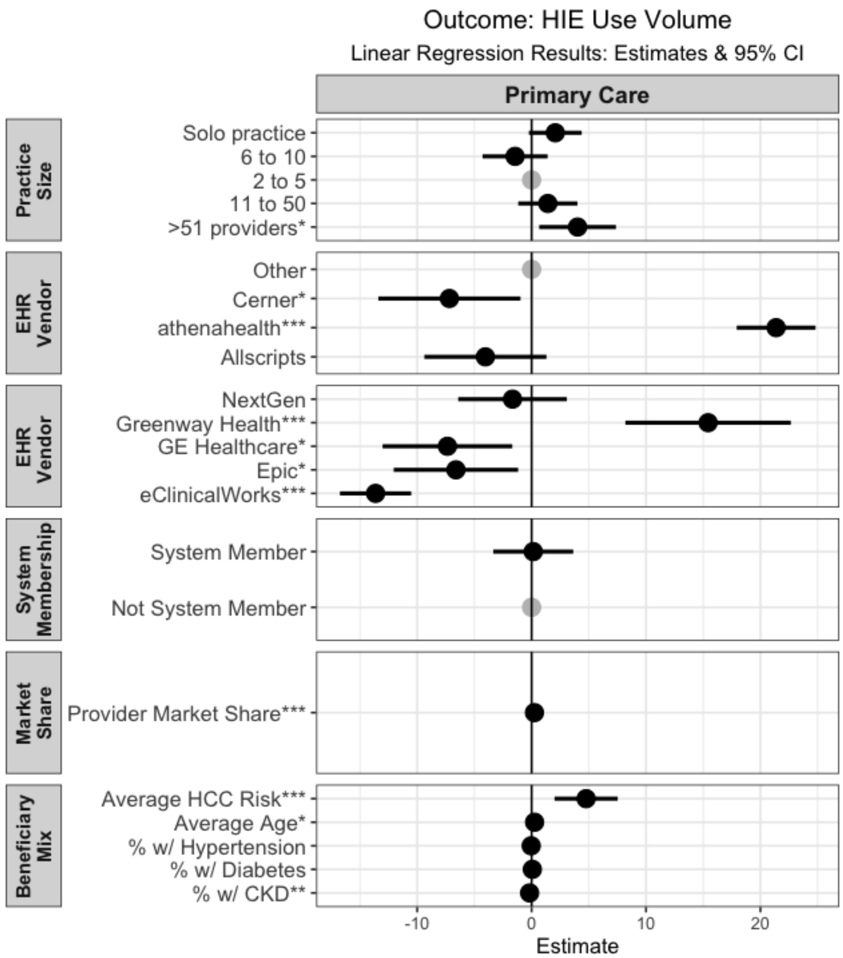


Figure 2.2 Practice factors associated with HIE volume, primary care

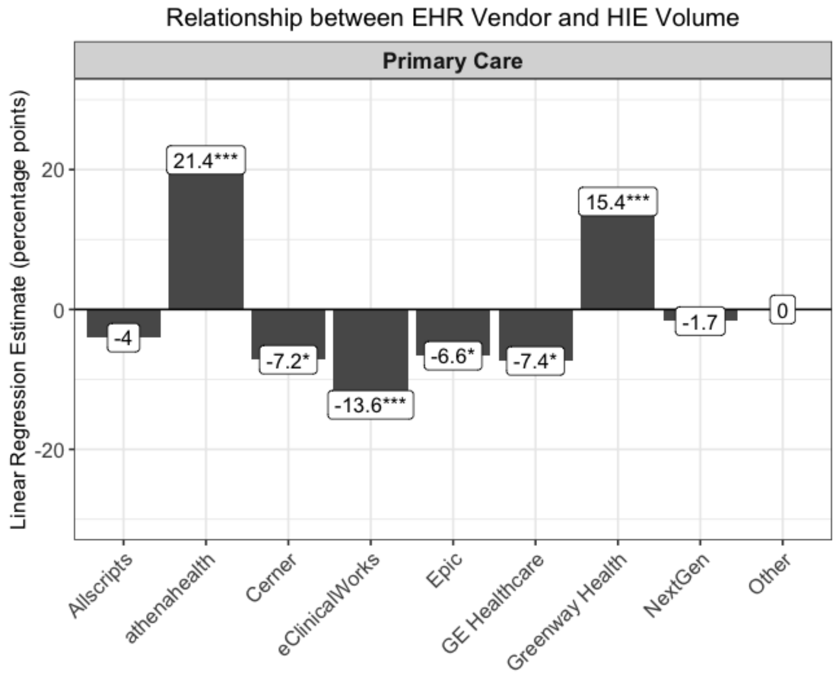


Notes: Forest plot displays results from linear regression estimates of the relationship between practice factors and provider HIE use volume. HIE use volume is measured as the percentage of referrals sent with eSCR, reported to MU Stage 2 in 2016. Model adjusts for market factors and controls for provider gender and years in practice. Significance levels: *p<0.05 **p<0.01 ***p<0.001. Results for cardiology and orthopedic surgery can be found in Table 2.1 and in Appendix A, figures A3 and A5, respectively.

Practice Factors

In regression analyses, the practice factor most consistently associated with HIE volume across provider groups was EHR vendor (Table 2.1). For primary care providers, use of Cerner, Epic Systems, eClinicalWorks, or GE Healthcare was negatively associated with HIE volume (Figure 2.2). These negative relationships ranged in magnitude from -13.6 percentage points (eClinicalWorks, $p<0.001$) to -6.6 percentage points (Epic Systems, $p=0.017$). EHR vendors athenahealth (21.4pp, $p<0.001$) and Greenway Health (15.4pp, $p<0.001$) were positively associated with HIE volume, compared to other EHR vendors (Figure 2.3). Within the sample of cardiologists, Cerner and GE Healthcare demonstrated a negative relationship with HIE volume (-12.3pp, $p=0.06$ & -18.8pp, $p=0.003$). Use of Cerner was also negatively correlated with HIE volume for orthopedic surgeons (-25.8pp, $p<0.001$), as was Epic Systems (-11.7pp, $p=0.049$) and NextGen Healthcare (-11.3pp, $p=0.008$). Within the surgeon sample, Greenway Health had a positive associate with HIE volume (29.6pp, $p<0.001$).

Figure 2.3 Relationship between EHR vendor and HIE volume, primary care



Notes: All estimates adjust for practice and market factors, as well as for provider years in practice and gender. All estimates are relative to providers with EHRs not in the top eight most common (i.e. "Other"). Plot does not show 95% confidence intervals for estimates. Significance levels: *p<0.05 **p<0.01 ***p<0.001. See Figure 2 and/or Table 2.1 for complete results. HIE Volume is measured as the percentage of patient referrals sent with eSCR. Results for Cardiology and Orthopedic Surgery can be found in Appendix Figures A1 and A2, respectively.

Larger practice sizes were associated with greater rates of referrals send with eSCR for both primary care providers and cardiologists, compared to practices with between 2 and 5 providers. Primary care practices with more than 51 providers had 4pp higher HIE volume, on average, compared to practices with 2-5 providers (p=0.019).

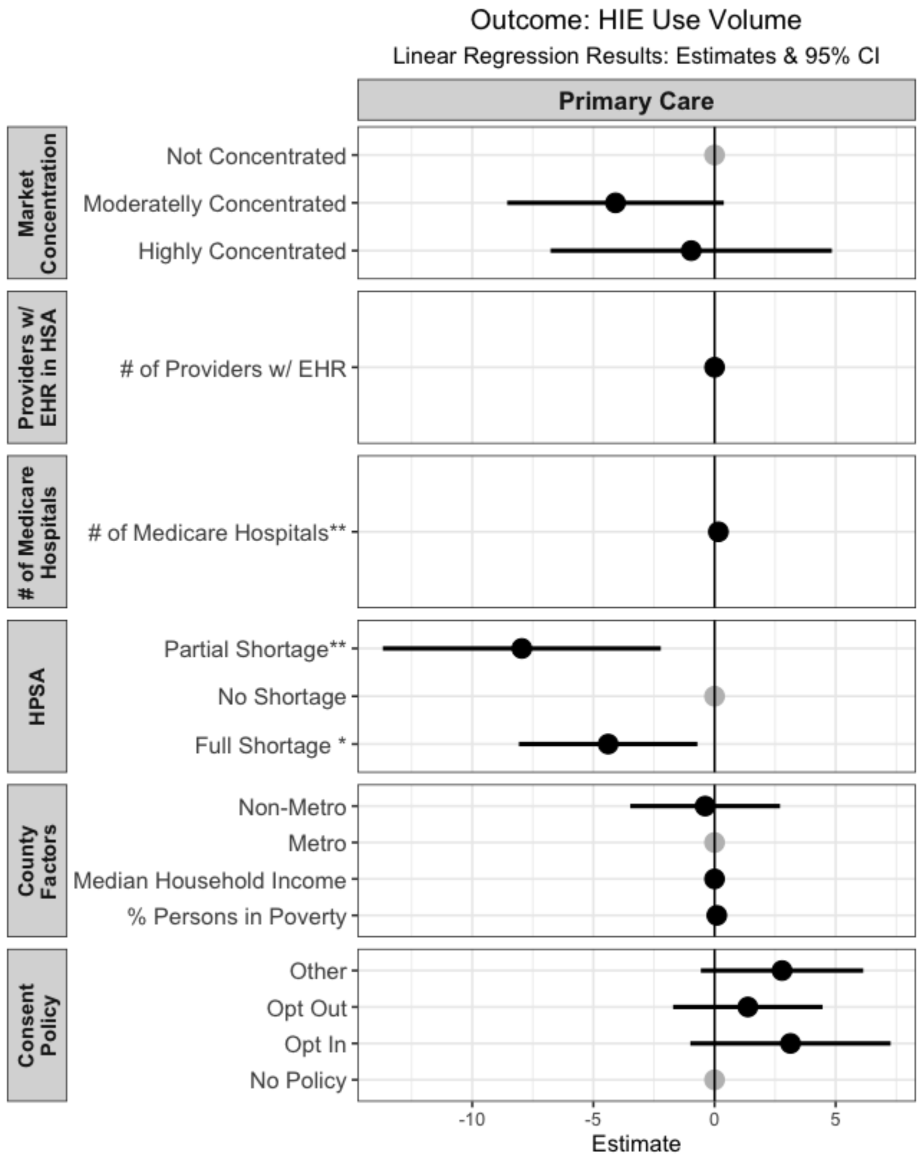
Cardiologists in practices with 11 to 50 providers had 12.9pp higher HIE use volume (p=0.002).

Health system membership was associated with HIE volume only in the cardiology provider group; providers affiliated with health systems sent referrals with eSCR in 7.3pp more cases (p=0.019). For primary care providers, average beneficiary age (0.3pp, p=0.042) and average beneficiary HCC risk scores were both positively associated with volume of HIE, with each additional point on the HCC risk scale associated with 4.8pp more referrals sent with eSCR (p<0.001).

Market Factors

Relative to practice factors, few market factors were associated with HIE use volume for providers across the three specialty groups. For primary care providers, the number of Medicare hospitals was positively associated with HIE volume (0.2pp, p=0.009, Figure 2.4). Furthermore, primary care providers located in counties classified as either partial or full health professional shortage areas illustrated lower levels of HIE volume (-8.0pp, p=0.007 & -4.4pp, p=0.019). This relationship for full health professional shortage areas was more pronounced among cardiologists, who sent referrals with eSCR in 15.3pp fewer cases (p<0.001), compared to counties with no shortage in health professionals. Across all three provider groups, market concentration, number of providers in the HSA with EHRs, non-metropolitan location, and state HIE consent policy were unrelated to provider HIE volume. We found no market factors to be associated with HIE volume for orthopedic surgeons.

Figure 2.4 Market factors associated with HIE volume, primary care



Notes: Forest plot displays results from linear regression estimates of the relationship between market factors and provider HIE use volume. HIE use volume is measured as the percentage of referrals sent with eSCR, reported to MU Stage 2 in 2016. Model adjusts for practice factors and controls for provider gender and years in practice. Significance levels: *p<0.05 **p<0.01 ***p<0.001. Results for cardiology and orthopedic surgery can be found in Table 2.1 and in Appendix A, figures A4 and A6, respectively.

Table 2.1 Regression results: practice and market factors associated with HIE volume

		Primary Care		Cardiology		Orthopedic Surgery	
		B [95% CI]	*p*	*B [95% CI]*	*p*	*B [95% CI]*	*p*
Practice Factors							
Practice Size	2 to 5	reference		reference		reference	
	>51 providers	**4 [0.7,7.4]***	0.019	8.4 [-0.3,17.1]	0.059	5.4 [-2.5,13.2]	0.183
	11 to 50	1.4 [-1.2,4]	0.282	**12.9 [4.7,21.2]****	0.002	2.5 [-5,10.1]	0.51
	6 to 10	-1.4 [-4.3,1.4]	0.32	8.2 [-2.1,18.4]	0.119	-1.2 [-11,8.5]	0.803
	Solo practice	2.1 [-0.2,4.4]	0.078	4 [-6.3,14.2]	0.448	-0.9 [-10.5,8.8]	0.86
EHR Vendor	other	reference		reference		reference	
	Allscripts	-4 [-9.4,1.3]	0.138	0.8 [-15.9,17.5]	0.925	-1.4 [-11.7,8.8]	0.784
	athenahealth, Inc.	**21.4 [17.9,24.8]*****	p<0.001	-12 [-25.1,1.1]	0.074	-7.3 [-15,0.3]	0.06
	Cerner Corporation	**-7.2 [-13.4,-1]***	0.023	**-12.3 [-20.9,-3.6]****	0.006	**-25.8 [-37.8,-13.8]*****	p<0.001
	eClinicalWorks, LLC	**-13.6 [-16.7,-10.5]*****	p<0.001	4.4 [-1.2,10]	0.12	-9.6 [-20.2,0.9]	0.073
	Epic Systems Corporation	**-6.6 [-12,-1.2]***	0.017	-0.1 [-15.4,15.2]	0.991	**-11.7 [-23.4,0]***	0.049
	GE Healthcare	**-7.4 [-13,-1.7]***	0.011	**-18.8 [-31.1,-6.5]****	0.003	-14 [-31.8,3.8]	0.124
	Greenway Health, LLC	**15.4 [8.2,22.7]*****	p<0.001	11.2 [-0.4,22.7]	0.058	**29.6 [20,39.2]*****	p<0.001
	NextGen Healthcare	-1.7 [-6.4,3.1]	0.491	-8.6 [-17.3,0.1]	0.052	**-11.3 [-19.7,-3]****	0.008
Health System Membership	Not in a health system	reference		reference		reference	
	In a health system	0.1 [-3.4,3.6]	0.936	**7.3 [1.2,13.4]***	0.019	-2.2 [-8.2,3.7]	0.463
Provider Market Share (w/in specialty)		**0.3 [0.1,0.4]*****	p<0.001	0 [-0.1,0.1]	0.99	-0.1 [-0.3,0]*	0.01
Average Beneficiary Age		**0.3 [0,0.5]***	0.042	-0.7 [-1.8,0.4]	0.228	0.2 [-0.7,1.1]	0.676
Average Beneficiary HCC Risk Score		**4.8 [2,7.5]*****	p<0.001	-3.4 [-17.5,10.6]	0.632	-8.6 [-23.6,6.4]	0.259
% of Beneficiaries w/ CKD		**-0.2 [-0.3,-0.1]****	0.002	0.2 [-0.4,0.7]	0.551	-0.2 [-0.7,0.4]	0.573
% of Beneficiaries w/ Diabetes		0.1 [-0.1,0.2]	0.325	-0.3 [-0.8,0.1]	0.15	**0.7 [0.3,1.2]*****	p<0.001
% of Beneficiaries w/ Hypertension		0 [-0.2,0.1]	0.557	0.7 [-0.8,2.2]	0.384	-0.2 [-0.6,0.3]	0.458
Market Factors							

HSA Concentration Index	Unconcentrated	reference		reference		reference	
	Moderately Concentrated	-1 [-6.8,4.8]	0.745	-5.9 [-13.4,1.7]	0.131	5.6 [-1.2,12.4]	0.108
	Highly Concentrated	-4.1 [-8.6,0.4]	0.073	4.3 [-2.9,11.5]	0.241	1.6 [-4.5,7.7]	0.614
Number of Providers with EHRs in HSA		0 [0,0]	0.477	0 [0,0]	0.44	0 [0,0]	0.829
Number of Medicare Hospitals, county		**0.2 [0,0.3]****	0.009	0 [-0.3,0.3]	0.922	0.1 [-0.2,0.4]	0.626
Health Professional Shortage Area	No Shortage	reference		reference		reference	
	Partial Shortage	**-8 [-13.7,-2.2]****	0.007	-4.2 [-21.2,12.7]	0.624	-2.3 [-17.5,13]	0.77
	Full Shortage	**-4.4 [-8.1,-0.7]***	0.019	**-15.3 [-21.5,-9]*****	p<0.001	2.9 [-4.3,10]	0.432
Median Household Income, county		0 [0,0]	0.928	**0 [0,0]*****	p<0.001	0 [0,0]	0.183
Percent of Persons in Poverty, county		0.1 [-0.3,0.5]	0.637	**1 [0.1,2]***	0.033	-0.2 [-1,0.6]	0.592
Metro vs. Non-Metro (%)	Metro	reference		reference		reference	
	non-Metro	-0.4 [-3.5,2.7]	0.806	-4.4 [-11.2,2.3]	0.198	-0.3 [-7.1,6.4]	0.925
State HIE Consent Policy	NoPolicy	reference		reference		reference	
	OptIn	3.1 [-1,7.3]	0.137	-4.9 [-11.7,1.9]	0.16	-0.3 [-6.8,6.2]	0.933
	OptOut	1.4 [-1.7,4.5]	0.383	1.2 [-6,8.3]	0.751	-1.8 [-9.4,5.8]	0.643
	Other	2.8 [-0.6,6.1]	0.103	-2.8 [-9.9,4.4]	0.448	-1.1 [-7.5,5.2]	0.731
Control Variables							
Provider Gender	F	reference		reference		reference	
	M	-0.8 [-1.7,0.2]	0.103	1.4 [-3.2,6]	0.549	-4.6 [-13.3,4.1]	0.301
Years in Practice		**0.1 [0,0.1]****	0.003	0.1 [0,0.2]	0.138	-0.1 [-0.2,0.1]	0.301
	Constant	21 [-1.7,43.6]	0.07	42.2 [-98.4,182.9]	0.556	41.4 [-36.1,118.9]	0.295
	AIC	197702		20279		13726	
	n	21,178		2,116		1,454	

Notes: Significance levels: *p<0.05 **p<0.01 ***p<0.001. All models use robust standard errors clustered at the practice level.

Model Robustness

In the Heckman sample selection model, our identification variable of 2015 exclusion status served as a significant predictor of selection into the sample for all three provider subgroups (β_{PCP}=-1.73, p<0.001; β_{Card}=-1.83, p<0.001; β_{Ortho}=-1.88, p<0.001). We found moderate evidence of sample selection bias among primary care providers using the altrho ($\boldsymbol{\rho}$) statistic to test the correlation between the errors of the first stage (sample selection) model and those of the second stage (OLS) model ($\boldsymbol{\rho}_{PCP}$ = -0.0797, p=0.031) [2.29]. We did not observe this for cardiologists or orthopedic surgeons ($\boldsymbol{\rho}_{Card}$ = 0.015, p=0.794; $\boldsymbol{\rho}_{Ortho}$ = -0.0253, p=0.732). The negative $\boldsymbol{\rho}$ value for primary care providers is consistent with the anticipated finding that those who received an exclusion for this measure had a lower predicted volume of HIE than providers whom we observe in the sample. Furthermore, and consistent with the low magnitude of bias present in the primary care sample, we found that the estimates from the second stage of the Heckman model differed only trivially from the primary analysis results described above (Appendix A, Tables A3, A4, & A5). This lack of difference combined with the lack of evidence of bias among cardiologists and orthopedic surgeons motivated our choice to report the primary OLS results for all provider subgroups rather than the Heckman adjusted results.

Discussion

We analyzed national data on provider HIE use volume reported to MU Stage 2 in 2016. We find that, on average, providers outperformed the minimum threshold set by CMS of 10% of patient referrals sent with eSCR. Overall, 45% of referrals were sent with eSCR, suggesting that providers used HIE at higher rates given the infrastructure for exchange was available. While MU Stage 3 proposals had planned to increase the required eSCR threshold for providers to 30% of referrals [2.30], subsequent regulatory revisions incorporated into the Merit-Based Incentive Payment System (MIPS) and Promoting Interoperability (PI) programs have reduced this requirement to the original MU Stage 1 requirement to send an eSCR for only 1 patient referral during the reporting period for the 2017-2020 program years [2.31]. Requirements for MU Stage 1 and Stage 2 were set intentionally low, in order to prioritize the high early-stage investment needed to first create a network of providers with the capability to exchange information. At the outset, the incentives for Stage 3 and beyond were designed to incentivize the widespread use of this network. Recent policy revisions may reflect an initial under-estimate of the costs and available resources to establish HIE capabilities in office-based practices. It is not clear whether this reduced regulatory burden will impact the volume of HIE among providers, however our results suggest that the majority of providers do not merely meet the minimum threshold, conditional on the capability to send eSCRs. While we observe higher than minimum rates of HIE use in our provider sample, it is important to note that more than 40,000 providers from the three selected specialty groups received an exclusion from reporting this measure in 2016 and are thus out of our sample. These providers may differ from our sample in unobserved but important ways (e.g. in adoption of HIE capabilities) and thus our findings do not shed light on HIE volume among these exempted providers.

Among providers reporting HIE volume, practice characteristics were more commonly associated with HIE volume than market characteristics. In particular, we observed large and statistically significant relationships between the EHR vendor each practice used and HIE volume. Primary care providers using athenahealth for their EHR sent eSCRs with, on average, 21 percentage points more referrals than providers using other EHR vendors not in the top eight most common vendors. More troubling, we observe far more negative relationships between major EHR vendors and HIE volume. The two largest inpatient EHR vendors, Cerner and Epic Systems, both demonstrate consistent negative relationships with HIE volume in our provider sample. Given that our analysis focuses on providers who are not primarily located in inpatient settings, this finding may reflect HIE workflows within these EHRs that are designed for inpatient care and thus are more challenging for outpatient providers. A similar study examining hospital level of HIE using the same nationwide MU Stage 2 data for hospitals found that hospitals using Epic sent 7 percentage points more transfers with eSCR [2.11], suggesting that inpatient-focused EHRs may facilitate HIE volume in inpatient settings, while outpatient-focused EHRs - such as athenahealth - better facilitate HIE among outpatient providers. This setting-vendor match should be considered in future studies seeking to compare the use of health IT across vendors and across settings, as some proportion of EHR vendor-level findings may be rooted in workflows not matched for the setting in which the EHR is used.

We found that primary care providers who saw, on average, more complex patients (as measured by average HCC risk score) sent referrals with eSCR at higher rates. This finding fits with prior studies finding that HIE use is more likely for more complex patients [2.32,2.33]. Furthermore, we do not see this effect for cardiologists or surgeons, highlighting possible differences in HIE use for complex patients between providers who are more commonly distributing information (e.g. primary care providers) from those who predominantly receive information (e.g. specialists). Because primary care providers often must take on this role of care coordinators for complex patients [2.34,2.35], having systems in place to send patient information collected in primary care to other providers is particularly important for realizing a return on the collective national investment in health IT. In parallel, it may be more important to ensure that specialists have the ability to effectively receive information, especially as it pertains to more complex patients, who may be more likely to have information sent electronically with their referrals.

We found few market-level factors to be related to provider HIE volume across specialty groups. In particular, the lack of relationship between market concentration and HIE volume suggests that anti-competitive information sharing behavior among providers may not be a contributing factor to the volume of HIE in a given market. While previous studies of hospitals have shown that adoption of HIE and presence of health information organizations is lower in more competitive markets [2.36–2.38], our findings illustrate that, among providers with the capability to exchange, HIE volume does not differ across HSAs with varying levels of market concentration. If anti-competitive behavior was related to HIE volume, one would expect more highly concentrated markets (i.e. less competitive markets) to have higher rates of HIE, compared to more competitive markets where providers stand to lose from broad information sharing. This finding, in conjunction with previous work failing to find a relationship between market competition and hospital level of HIE [2.11,2.24], suggests that while HIE adoption decisions may be a function of market concentration, once adoption has occurred, competition does not appear to impact the level of HIE among providers or hospitals. As a result, regulatory efforts to combat anti-competitive information sharing behavior may be most effective when focused on adoption of HIE capabilities, rather than on the volume of HIE that occurs among entities with these capabilities; recent updates to the MIPS and PI programs noted above reflect this programmatic focus. A policy focus on adoption and HIE capabilities is further supported by the lack of a relationship between state HIE consent policy and provider HIE volume, consistent with prior literature studying hospitals [2.24]. While provider HIE volume seems to be unrelated to specific policy choices (in this case regarding consent), policy choices may facilitate or hinder provider adoption of HIE capabilities, as has been illustrated in previous studies of hospitals [2.24,2.39,2.40].

Finally, both primary care providers and cardiologists located in counties classified as “full shortage” by HRSA illustrated lower HIE volume, compared to those in counties with no provider shortage. This finding may reflect a relative lack of viable partners for exchange in the region, a factor that has not been shown to impact hospital HIE volume [2.11].

Taken together with the existing literature, these findings have important implications for policy-makers aiming to design a regulatory environment that fosters widespread HIE between providers and hospitals. Primarily, our findings illustrate that eSCRs are sent in less than half of all patient referrals, even among providers with these capabilities. This is likely to be an overestimate of the true national rate of eSCR use, as only one-third of providers report even having the ability to send eSCRs. To realize the potential return on the investment to-date in health IT, HIE capabilities among providers and subsequent use of HIE will likely need to increase. Furthermore, our analysis makes clear that among providers who have these capabilities, practice factors like EHR vendor and patient complexity play an important role with respect to HIE volume, and this variation should be reflected in the regulatory incentives put in place via the MIPS and PI programs. Finally, our findings suggest that there may be EHR vendor-specific factors that facilitate or hinder provider HIE and that these factors may vary across provider settings. For example, an EHR vendor whose main product is focused on inpatient settings may need to specifically examine outpatient HIE workflows to reach HIE volume parity with EHRs that are predominantly focused on outpatient provider markets.

Limitations

Our study has both strengths and limitations. To our knowledge, this is the first nation-wide study to examine provider volume of HIE use, as measured by provider MU Stage 2 attestation data. Additionally, we combined several public data sources to construct a sample that controls for observable confounding effects. Moreover, the current study is the first to directly examine the relationship between practice and market factors and HIE volume among office-based providers. Our sample of providers represents primary care, medical specialties, and surgical providers, and as such reflects important differences in HIE volume and provides insight into variation across different provider groups in the factors related to HIE volume. Finally, we use a measure of HIE use that is both more granular than many survey measures and is explicitly tied to policy goals for HIE use set by federal incentive programs.

Even considering these strengths, our study is inherently limited in that it is cross-sectional, and therefore all relationships must be understood as associative rather than causal. Furthermore, our study captures a snapshot of HIE use as of 2016. Provider practices are regularly increasing their technological capabilities with respect to HIE, and community HIE efforts have continued to facilitate more exchange of clinical data among a growing number of partner organizations. Additionally, the providers in our sample may not be generalizable to the overall Medicare physician population, as the sample consists of providers attesting to MU Stage 2 in 2016 who did not receive an exemption from the HIE measure (more than half of providers received this exemption). As such, interpretation of our results should consider the fact that our sample, by definition, has the capability to send eSCRs, which only 36% of office-based providers nationwide reported in 2017 [2.8]. Therefore, our findings provide insight on HIE volume conditional on providers' ability to exchange data.

Conclusion

We used nationwide data measuring provider HIE volume among primary care providers, cardiologists, and orthopedic surgeons to analyze the relationship between HIE volume and practice and market factors. We found that on average less than half of referrals are sent with eSCR documents. Furthermore, practice factors like EHR vendor and patient complexity were related to HIE volume, with heterogeneous effects across provider groups. Fewer market factors played a role in provider HIE volume, suggesting that market forces may impact adoption of HIE capabilities more than they impact provider use of HIE once it is adopted. To foster more use of HIE across the health care system, policy-makers should consider the relative impact that market factors may have on adoption, compared to practice-level factors that are related to the use of HIE more directly. Future research may explore in more detail the nature of the relationship between provider EHR vendor and HIE volume, as well as the varying health IT needs of providers who may primarily send or primarily receive health data.

References

2.1 Verma S. Remarks by CMS Administrator Seema Verma at the HIMSS18 Conference. 2018.https://www.cms.gov/Newsroom/MediaReleaseDatabase/Press-releases/2018-Press-releases-items/2018-03-06-2.html (accessed 5 Jul 2018).

2.2 Cross DA, Nong P, Harris-Lemak C, et al. Practice strategies to improve primary care for chronic disease patients under a pay-for-value program. Healthc (Amst) 2019;7:30–7. doi:10.1016/j.hjdsi.2018.08.004

2.3 Lin SC, Hollingsworth JM, Adler-Milstein J. Alternative payment models and hospital engagement in health information exchange. Am J Manag Care 2019;25:e1–6.https://www.ncbi.nlm.nih.gov/pubmed/30667611

2.4 Walker J, Pan E, Johnston D, et al. The value of health care information exchange and interoperability. Health Aff 2005;Suppl Web Exclusives:W5–10 – W5–18. doi:10.1377/hlthaff.w5.10

2.5 Vest JR, Gamm LD. Health information exchange: persistent challenges and new strategies. J Am Med Inform Assoc 2010;17:288–94. doi:10.1136/jamia.2010.003673

2.6 Adler-Milstein J, Jha AK. HITECH Act Drove Large Gains In Hospital Electronic Health Record Adoption. Health Aff Published Online First: 5 September 2017.http://www.healthaffairs.org/doi/10.1377/hlthaff.2016.1651 (accessed 9 Nov 2017).

2.7 Myrick KL, Ogburn DF, Ward BW. Table. Percentage of office-based physicians using any electronic health record (EHR)/electronic medical record (EMR) system and physicians that have a certified EHR/EMR system, by U.S. state: National Electronic Health Records Survey, 2017. National Center for Health Statistics 2019. https://www.cdc.gov/nchs/data/nehrs/2017_NEHRS_Web_Table_EHR_State.pdf

2.8 Patel V, Pylypchuk Y, Parasrampuria S, et al. Interoperability among Office-Based Physicians in 2015 and 2017. Office of the National Coordinator for Health IT 2019. https://www.healthit.gov/sites/default/files/page/2019-05/ONC-Data-Brief-47-Interoperability-among-Office-Based-Physicians-in-2015-and-2017.pdf

2.9 Dobrow MJ, Bytautas JP, Tharmalingam S, et al. Interoperable Electronic Health Records and Health Information Exchanges: Systematic Review. JMIR Med Inform 2019;7:e12607. doi:10.2196/12607

2.10 Menachemi N, Rahurkar S, Harle CA, et al. The benefits of health information exchange: an updated systematic review. J Am Med Inform Assoc Published Online First: 28 April 2018. doi:10.1093/jamia/ocy035

2.11 Lin SC, Everson J, Adler-Milstein J. Technology, Incentives, or Both? Factors Related to Level of Hospital Health Information Exchange. Health Serv Res Published Online First: 28 February 2018. doi:10.1111/1475-6773.12838

2.12 Holmgren AJ, Adler-Milstein J, McCullough J. Are all certified EHRs created equal? Assessing the relationship between EHR vendor and hospital meaningful use performance. J Am Med Inform Assoc 2018;25:654–60. doi:10.1093/jamia/ocx135

2.13 Mello MM, Adler-Milstein J, Ding KL, et al. Legal Barriers to the Growth of Health Information Exchange-Boulders or Pebbles? Milbank Q 2018;96:110–43. doi:10.1111/1468-0009.12313
2.14 Monestime JP, Biener AI, Wolford M, et al. Characteristics of Office-Based Providers Associated with Secure Electronic Messaging Use: Achieving Meaningful Use. Int J Med Inform Published Online First: 4 April 2019. doi:10.1016/j.ijmedinf.2019.04.002
2.15 Medicare Provider Utilization and Payment Data: Physician and Other Supplier. Centers for Medicare and Medicaid Services. 2018.https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/Physician-and-Other-Supplier.html (accessed 17 May 2019).
2.16 Schmit CD, Wetter SA, Kash BA. Falling short: how state laws can address health information exchange barriers and enablers. J Am Med Inform Assoc 2018;25:635–44. doi:10.1093/jamia/ocx122
2.17 Compendium of U.S. Health Systems, 2016. https://www.ahrq.gov/chsp/data-resources/compendium-2016.html (accessed 5 Apr 2020).
2.18 Richards MR, Smith CT, Graves AJ, et al. Physician Competition in the Era of Accountable Care Organizations. Health Serv Res 2018;53:1272–85. doi:10.1111/1475-6773.12690
2.19 Heisey-Grove DM, Wall HK, Wright JS. Electronic clinical quality measure reporting challenges: findings from the Medicare EHR Incentive Program's Controlling High Blood Pressure Measure. J Am Med Inform Assoc 2018;25:127–34. doi:10.1093/jamia/ocx049
2.20 EHR Products Used for Meaningful Use Attestation. Office of the National Coordinator for Health Information Technology | Dashboards. https://dashboard.healthit.gov/datadashboard/documentation/ehr-products-mu-attestation-data-documentation.php (accessed 6 Mar 2018).
2.21 HUD USPS ZIP Code Crosswalk Files. United States Department of Housing and Urban Development. https://www.huduser.gov/portal/datasets/usps_crosswalk.html (accessed 17 May 2019).
2.22 Herfindahl-Hirschman Index. United States Department of Justice. 2015.https://www.justice.gov/atr/herfindahl-hirschman-index (accessed 17 May 2019).
2.23 Area Health Resources Files. Health Resource and Services Administration. https://data.hrsa.gov/topics/health-workforce/ahrf (accessed 12 Feb 2019).
2.24 Apathy NC, Holmgren AJ. Opt-in consent policies: potential barriers to hospital health information exchange. Am J Manag Care 2020.
2.25 Dow WH, Norton EC. Choosing between and interpreting the Heckit and two-part models for corner solutions. Health Serv Outcomes Res Methodol 2003;4:5–18.https://idp.springer.com/authorize/casa?redirect_uri=https://link.springer.com/article/10.1023/A:1025827426320&casa_token=EaJdKestz7UAAAAA:vEvIQJOr4dewsdzi3xVfAFCHj-Yz5DCp-z_nJbmAUZiStCjrXq4Bu6OMNQcW0d6cpCRjedRCBPzfLwmn
2.26 RStudio Team. R Studio. 2015. http://www.rstudio.com/

2.27 R Core Team. R: A Language and Environment for Statistical Computing. Vienna, Austria: : R Foundation for Statistical Computing 2018. https://www.R-project.org/
2.28 StataCorp LLC. Stata: Statistics/data analysis (Version 15: 1 IC edition). College Station, TX: StataCorp LLC 2017.
2.29 Certo ST, Busenbark JR, Woo H-S, et al. Sample selection bias and Heckman models in strategic management research. Strat Mgmt J 2016;37:2639–57. doi:10.1002/smj.2475
2.30 Cohen GR, Adler-Milstein J. Meaningful use care coordination criteria: Perceived barriers and benefits among primary care providers. J Am Med Inform Assoc 2016;23:e146–51. doi:10.1093/jamia/ocv147
2.31 Centers for Medicare and Medicaid Services. Explore Measures - Health Information Exchange. Promoting Interoperability - QPP. https://qpp.cms.gov/mips/explore-measures/promoting-interoperability?py=2019&measureObjectiveName=Health%20Information%20Exchange (accessed 22 Nov 2019).
2.32 Vest JR, Zhao H, Jasperson J, et al. Factors motivating and affecting health information exchange usage. J Am Med Inform Assoc 2011;18:143–9. doi:10.1136/jamia.2010.004812
2.33 Vest JR, Jasperson 'jon Sean, Zhao H, et al. Use of a health information exchange system in the emergency care of children. BMC Med Inform Decis Mak 2011;11:78. doi:10.1186/1472-6947-11-78
2.34 Savoy A, Militello L, Diiulio J, et al. Cognitive requirements for primary care providers during the referral process: Information needed from and interactions with an electronic health record system. Int J Med Inform 2019;129:88–94. doi:10.1016/j.ijmedinf.2019.05.027
2.35 Rothman AA, Wagner EH. Chronic illness management: what is the role of primary care? Ann Intern Med 2003;138:256–61. doi:10.7326/0003-4819-138-3-200302040-00034
2.36 Vest JR. More than just a question of technology: factors related to hospitals' adoption and implementation of health information exchange. Int J Med Inform 2010;79:797–806. doi:10.1016/j.ijmedinf.2010.09.003
2.37 Desai S. Health Information Exchange, Interoperability, and Network Effects. 2015.https://repository.upenn.edu/edissertations/1040/ (accessed 15 Apr 2018).
2.38 Lin SC, Adler-Milstein J. The relationship between hospital and ehr vendor market dynamics on health information organization presence and participation. BMC Med Inform Decis Mak 2018;18:28. doi:10.1186/s12911-018-0605-y
2.39 Brown-Podgorski BL, Hilts KE, Kash BA, et al. The Association Between State-Level Health Information Exchange Laws and Hospital Participation in Community Health Information Organizations. AMIA Annu Symp Proc 2018;2018:313–20.https://www.ncbi.nlm.nih.gov/pubmed/30815070
2.40 Adjerid I, Acquisti A, Telang R, et al. The Impact of Privacy Regulation and Technology Incentives: The Case of Health Information Exchanges. Manage Sci 2016;62:1042–63. doi:10.1287/mnsc.2015.2194

Chapter 3: Team-based use of HIE in primary care

Introduction

To improve care coordination and reduce the negative impact of care fragmentation, efforts such as the National Committee for Quality Assurance (NCQA) Patient-Centered Medical Home (PCMH) model [3.1] emphasize team-based and whole person care. Team-based care involves at least two clinical providers at the same primary care site working collaboratively with the patient towards shared health goals. Whole person care embraces a comprehensive understanding of patient health that transcends the normally fragmented view of the patient that the US health care system typically can provide. Both of these approaches require information sharing within care teams at a single site as well as between different provider teams and specialists caring for the same patient [3.2,3.3]. To support this information sharing, PCMHs rely on advanced health information technology (IT) to facilitate intra-team communication, care coordination efforts with outside providers, and distribution of clinical tasks across team members [3.4–3.8].

Studies of PCMHs have highlighted the importance of interoperable health information technology (IT) for supporting the goal of successful care coordination [3.3, 3.4,3.9,3.10], yet literature is scant regarding the extent to which this technology has been applied in practice to support team-based and whole person care. For example, to support team-based care, these systems must be designed to support team-based clinical workflows. However, integrating interoperable health IT use into workflows remains a challenge [3.11], on top of existing challenges in implementing team-based workflows more broadly [3.7,3.12]. The extent to which team-based use of interoperable health IT occurs remains unknown, even in primary care settings like PCMHs that utilize team-based care models and possess the requisite capabilities [3.7]. Low rates of team-based interoperable health IT use in these ideally suited settings may reflect technology design gaps, persistent team-based workflow integration challenges, or both.

Furthermore, team-based interoperable health IT use has the potential to supply a broader array of patient information to the care team than interoperable health IT use by a single provider, thus informing whole-person care. Alternatively, one-size-fits-all workflows lacking design suited for specific care settings or roles may result in duplicative use across team members, and limit the breadth of information obtained by the team. Moreover, these workflows have been found to be a barrier to the use of interoperable health IT [3.11]. The extent to which interoperable health IT use by teams begets a broader array of patient information relative to non-team-based use remains unknown. Greater breadth among teams may illustrate the benefits of team-based use of interoperable health IT in particular for support of whole person care initiatives. Lack of variation in this measure may indicate barriers rooted in generic workflows (i.e. all users see the same information), parity in information needs (i.e. teams and single users seek the same information), or simply effective delegation (i.e. the team views the information that the single user would have viewed).

Finally, team-based use of interoperable health IT may result in more detailed or targeted ("deep") review of outside clinical data by team members with dedicated time to gather information. For example, a team member tasked with understanding a patient's emergency department (ED) utilization history may have more time than a primary care provider to look at specific ED visit notifications to understand more context and detail regarding that visit. However, the literature exploring use depth has yet to explore primary care settings or how depth varies between individual users and teams [3.13–3.15]. Similar to breadth, deeper use among teams may indicate the ability of interoperable health IT to support whole person care and a more detailed understanding of the patient's health history. Additionally, deeper team-based use may indicate appropriate task delegation that not only increases the care team's information but removes this task from the provider, which can improve job satisfaction and reduce burnout [3.16,3.17]. Alternatively, a lack of variation between single users and teams in depth could indicate that information needs in primary care are met by more summative, less deep use of interoperable health IT.

This study first seeks to quantify the extent of team-based use of interoperable health IT as compared to individual user use of these systems. Second, we compare the nature of team-based interoperable health IT usage to individual users as characterized by the breadth and depth of information accessed by the team. Detailed understanding of the use of technology in supporting team-based care may be valuable to organizations implementing health IT in support of care delivery redesign efforts. Furthermore, the success of delivery system reform efforts like the PCMH depends in part on identifying the role of delegation and task sharing to support care coordination [3.3,3.7]. Should we observe team-based use of health IT that mirrors single-user use, implementations may be taking place without respect to how team-based workflows differ from those of single users. Improvements to quality and health outcomes are unlikely to occur if technology use does not align with the models of care aiming to achieve those goals.

Methods

We used an observational, retrospective study design with data from a regional HIE to identify team-based use of the HIE system among users from three PCMHs in the Rochester, NY, region. We measured the prevalence of team-based HIE use, and quantified both breadth and depth of use among teams and non-teams. We then modeled the relationship between team-based HIE use and our two outcome variables: breadth and depth of HIE use, to analyze the degree to which HIE use among teams differs from provider HIE use, controlling for patient and visit characteristics. We stratified our analysis by timing of HIE use relative to the visit, conducting separate analyses for HIE use that took place in the two weeks prior to the visit, on the day of the visit, and in the two weeks following the visit.

Setting & Data

Study subjects are HIE users from three PCMH-recognized Federally Qualified Health Centers: Anthony Jordan Health Center (AJHC), Oak Orchard Community Health Center (OOCHC), and the Rochester Primary Care Network (RPCN), a network of health centers with more than 20 service locations. FQHCs are primary health care centers that receive funding from the Health Resources and Services Administration (HRSA) and provide care to underserved areas in the US [3.18]. All three sites have been recognized as a Level III PCMH by NCQA, meaning they have successfully implemented team-based care models, care management, and care coordination practices supported by certified health IT, including HIE. Beginning in 2014, PCMH standards included "access to a health information exchange" as an optional factor for PCMHs to count towards their overall score, which in turn determines the level of PCMH certification the practice receives.

The HIE system in our study is the Rochester Regional Health Information Organization (RHIO), a non-profit health information organization that provides HIE services to a 13-county region of western New York [3.19]. Users access the HIE database via a secure web portal in which they can query for individual patients and view clinical information from other health care organizations. The portal includes summative section-level pages such as an overall patient summary, laboratory results, and radiology results, among other clinical information categories. Furthermore, users can view details of specific result documents such as individual laboratory results and admission, discharge, and transfer (ADT) documents detailing visits to other providers. Additional background about the RHIO can be found in Appendix B.

We combined user log data from the HIE system with clinical EHR data capturing patient visits from January 2012 through December 2015. The HIE log data included discrete click-level observations logged for each action users took within the HIE web portal. Each observation in the log data included the page of the web portal on which the action took place, allowing for identification of the section or specific document type a user accessed while using the HIE (Appendix B, Table B1). Finally, the log data included timestamps, user identifiers and roles, and anonymized patient identifiers that allowed us to link the HIE use data with patient visits based on patient identifiers and date matching. More detail on the RHIO, user workflow, and data can be found in the Appendix.

We created a visit-level analytical sample by linking the HIE use data to clinical data from each site's EHR including patient gender, age, and indicator variables for 18 different primary diagnoses. These indicator variables were computed at the encounter level using the Agency for Healthcare Research and Quality's (AHRQ) Clinical Classification Software (CCS) based on the coded primary diagnosis for the visit [3.20]. Other visit data in the clinical EHR data included visit date and time, the date and time the patient made the appointment for visit, visit type, provider seen, and whether or not the visit was billable or non-billable.

Independent Variable: Team-Based HIE Use

We linked the two data sets by matching via the anonymized patient identifier, site, and visit date matching the date of the HIE use activity for that patient. Because HIE use may serve different purposes based on the timing of use relative to the encounter [3.21], we stratified our analysis to analyze team-based HIE use in the two weeks prior to a visit, the same day of the visit, and in the two weeks following the visit. We defined team-based HIE use as use of the HIE by a user with a different credential than the visit provider. This included system use by more than one user for the same patient. We defined team-based use as such because this HIE use pattern reflects task distribution across team members. Visits were classified as not having team-based HIE use if the patient's record was accessed by a single HIE user with the same credential as the visit provider. While we were not able to match individual care team members across the EHR and HIE use data, both data sources included the credential of the provider (in the EHR data) and the HIE user (e.g. MD or NP). By identifying single HIE users whose credential did not match that of the visit provider, we were able to identify HIE users who were not the visit provider.

Outcome Measures: HIE Use Breadth and Depth

We calculated two measures of the nature of HIE use to capture the extent to which team-based HIE use differed from HIE use that was not team-based. We chose measures of HIE use that could be calculated for both team-based and visit provider HIE use, to allow for comparison. First, we measured HIE use breadth by calculating the number of unique information categories the single user or team viewed in the HIE for a specific patient. We used the section and document type information in the HIE logs to identify the different sections or document types viewed in the HIE for a particular patient. We counted section-level use data and specific document viewing as separate information categories, even if the overarching type of clinical data was the same. For example, if a team member or members viewed the Summary tab, the Laboratory tab, and a specific laboratory result, that use would amount to three unique information categories. This definition is congruent with previous work by Cross (2018) defining use "intensity" and Politi, et al. (2014) in what they termed use "diversity" [3.22,3.23]. Second, we measured HIE use depth by calculating the proportion of total HIE use spent viewing specific documents. In this measure, the denominator was the total number of actions in the HIE for that patient across all HIE users. The numerator was the number of these actions that captured viewing of specific result or report documents. In this measure, greater document viewing as a proportion of total HIE activity represents greater levels of HIE use depth.

Control Variables: Visit and Patient Characteristics

We constructed four visit-level variables to address potential confounding of the relationship between our outcome variables and team size, visit duration, time since the visit was scheduled, and time since the patient's last visit. First, we constructed a variable for the total number of HIE users that accessed that patient's record in the HIE for that visit, as HIE use breadth in particular may be higher simply from more individuals accessing the HIE. Second, we used visit start and end time data from the scheduling system to calculate visit duration, which ranged from less than 15 minutes to over one hour. The vast majority of visits fell into the following five duration codes: 15 minutes, 20 minutes, 30 minutes, 45 minutes, and 60 minutes. We also included categories for visits lasting less than 15 minutes and more than 60 minutes, although those were rare. Longer visit durations, especially for same-day HIE use, may afford the team more time to view information in the HIE during the visit, thus confounding the relationship between team HIE use and the nature of that use. Third, we measured the days since the visit was scheduled, using a variable from the EHR data capturing visit scheduled date. This allowed us to differentiate between same day visits and those scheduled at various times prior to the visit, and served as a proxy for the amount of "lead time" the clinical team had before the visit took place, which may confound the relationship between team-based use and our outcomes. Finally, we constructed a variable measuring the time since the patient's last visit to the site, with the following levels: no past visit, greater than one year, prior year, prior 6 months, prior 90 days, and prior month. Previous studies have found that providers are more likely to access the HIE for "unfamiliar" patients and those without a visit in the previous year [3.24,3.25].

For patient-level characteristics, we include control variables for patient gender and age at visit and a binary indicator for whether or not the primary visit diagnosis was for a chronic condition, defined as hypertension, hyperlipidemia, coronary artery disease, congestive heart failure, diabetes mellitus, cancer, asthma, or chronic obstructive pulmonary disorder (COPD). Visit diagnoses for each encounter were identified using categorization by the CCS algorithm (Appendix B, Table B2).

Analysis

To calculate the prevalence of team-based HIE use across our entire sample, we divided the number of visits with any team-based HIE use by the total number of visits with any HIE use. Visits with no use were excluded from our analysis, as we sought only to examine variation in use within the sample of visits with HIE use. We stratified the measure by timing of use relative to the visit (2 weeks prior, same day, and 2 weeks after) to assess variation in team-based use before, during, and after visits. We used a chi-square test for differences in the prevalence of team-based HIE use, HIE use breadth, depth, and patient and visit characteristics across HIE use timing.

To estimate the relationship between team-based HIE use and use breadth, we used a negative binomial regression model with HIE use breadth (the count of unique information categories) as the dependent variable. Our primary independent variable was an indicator of team-based HIE use, compared to HIE use that was not team-based. We ran three regression models, one for each of the three use time periods. To estimate the relationship between team-based HIE use and use depth, we used a linear regression model with HIE use depth (the proportion of HIE activity spent viewing specific documents) as the dependent variable. For this model as well, our primary independent variable was the indicator of team-based HIE use, and we stratified our analysis over the three periods of use timing. All regression models adjusted for patient age at visit, patient sex, days since the last visit to the site, a binary indicator for whether or not the visit was for a chronic condition, the visit duration, the number of days since the visit was scheduled, and the number of HIE users. We included site (φ) and year (λ) fixed effects to account for time-invariant site characteristics and secular trends. All six models follow the form below:

$$\text{HIE Use Breadth/Depth}_v = \alpha + \beta_1\text{Team-BasedHIEUse}_v + \beta_2\text{AgeAtVisit}_v + \beta_3\text{PatientSex}_v + \beta_4\text{DasySinceLastVisit}_v + \beta_5\text{ChronicCondition}_v + \beta_6\text{VisitDuration}_v + \beta_7\text{DaysSinceVisitScheduled}_v + \beta_8\text{NumberOfHIEUsers}_v + \varphi_f + \lambda_t + \varepsilon_v$$

All data preparation and management, construction of HIE use measures, and analysis were done in the RStudio development environment [3.26] using the R statistical programming language [3.27]. The *tidyverse* suite of packages and *data.table* package were the primary software libraries used to construct the analytical data file [3.28,3.29]. The *glm* and *logitmfx* packages were used in the analysis portion [3.27]. The Indiana University Institutional Review Board approved this study.

Limitations

This study has a number of limitations. Chiefly, although we define measures of team-based HIE use, we are unable to formally validate these measures with respect to the exact data the user viewed. Specifically, the log data does not clarify which information a user was looking at on a given summary page or within a given document. The data also does not distinguish between different documents of the same type. For example, if we observe three actions in the context of a laboratory document, we do not know if the user took three actions on the same document or viewed three separate documents. Therefore, we are unable to validate precisely what patient information a user viewed within a given information category, similar to previous studies of HIE use

[3.14]. Furthermore, the definition of our comparison group, HIE use that is not team-based, is not perfectly matched across the two data sources; as such, our estimates of team-based HIE use rates likely understate the true rates. Second, in our analyses examining the relationship between HIE use breadth, depth, and team-based HIE use, estimates are subject to bias from unobserved, unmeasured confounding variables. While we adjust for patient and visit characteristics as well as static site characteristics and secular time trends, we are unable to control for unmeasured factors that could influence the relationships we estimate. Because the use of query-based HIE is voluntary, it is possible that the relationship between team-based HIE use and our outcome measures of the nature of HIE use are endogenous, and thus our findings may suffer from selection bias. Therefore, our results only describe associations between team-based HIE use and use breadth and depth.

Results

Rates of Team-Based HIE Use

Our final analytic sample included 12,556 unique visits in which the HIE was accessed either in the two weeks prior to the visit, the day of the visit, or in the two weeks after the visit. This reflects 3% of all visits to the three study sites during the study period, consistent with prior literature [3.30]. Of these visits with HIE use, 10,702 (85.2%) met our criteria for team-based use of the HIE, with a user or users other than the visit provider looking up information in the HIE for the patient in the two weeks prior to the visit, the day of the visit, or in the two weeks following the visit. We found differences in team-based HIE use rates across use timing relative to visit. In the two weeks prior to the visit, 88.1% of visits with any HIE use illustrated team-based use, while day-of-visit HIE use was less likely to be team-based (79.0%). Finally, in the two weeks following the visit, 85.9% of visits with HIE reflected team-based use of the HIE portal (Table 3.1, $\chi 2$ $p < 0.001$). A full table of descriptive results with rates of team-based HIE use, HIE use breadth, depth, and patient and visit characteristics stratified by use timing can be found in Appendix B, Table B3.

Table 3.1 Rates of team-based HIE use among visits with any HIE use

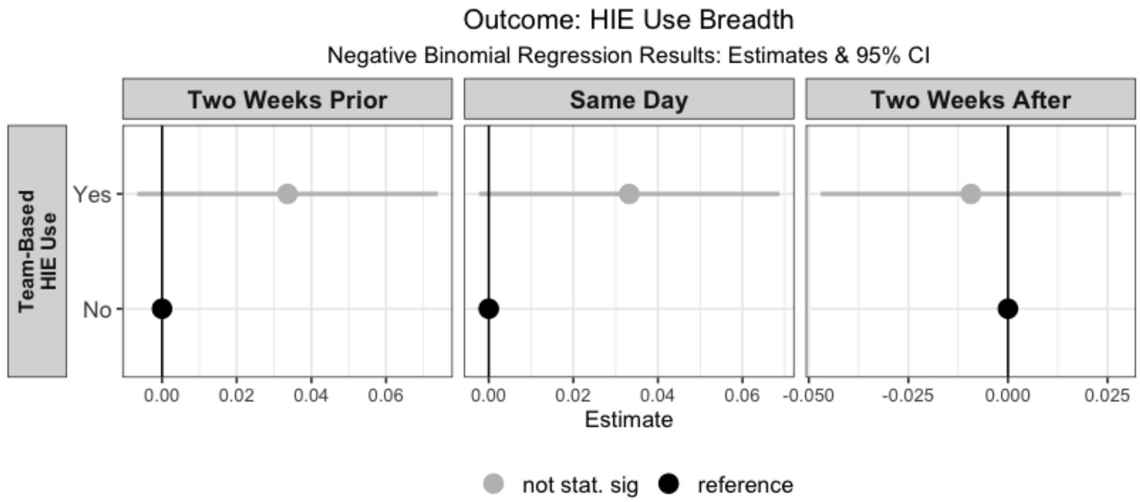
	Overall	**Two Weeks Prior**	**Day of Visit**	**Two Weeks After**
Total Visits w/ HIE Use	12,556	4,668	4,322	4,624
Visits w/ Team-Based HIE Use (%)	10,702 (85.2)	4,112 (88.1)	3,416 (79.0)	3,973 (85.9)

Notes: There were a total of 420,685 visits to the study sites during the study time period. 12,556 visits represents 3.0% of all visits, consistent with prior literature [23].

<u>HIE Use Breadth</u>

In regression analyses, team-based HIE use did not illustrate a relationship with HIE use breadth, adjusting for patient and visit characteristics (Figure 3.1, below). This finding held across all three time periods of HIE use relative to the visit ($ß_{-2wk}$=0.034, p=0.102; $ß_{sameday}$=0.033, p=0.067; $ß_{+2wk}$=-0.009, p=0.629). Full results for this analysis are presented in Appendix B, Table B4.

Figure 3.1 Team-based HIE use and HIE use breadth

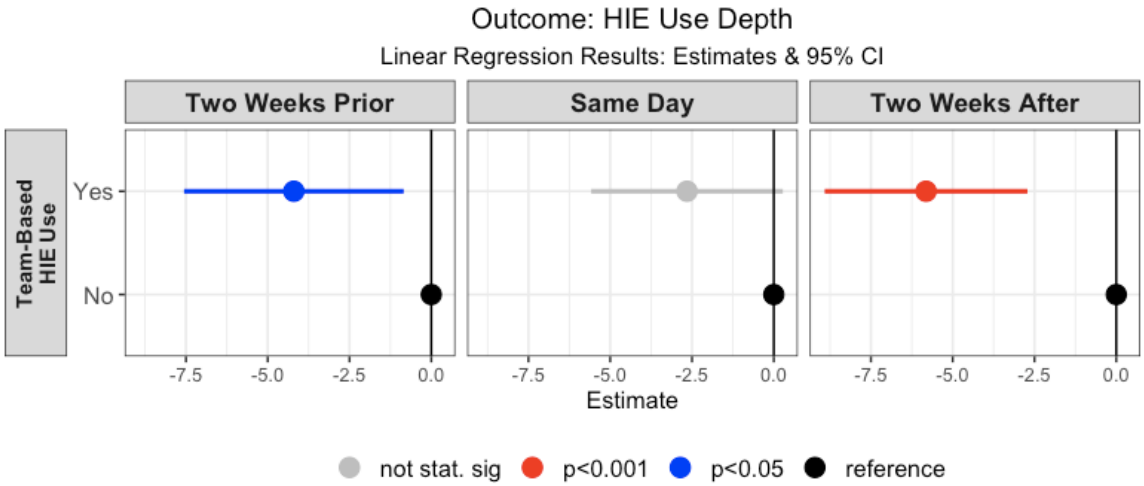


Notes: HIE use breadth is measured as the count of unique information categories viewed by the team or individual user. Models adjust for patient and visit characteristics as well as site and year fixed effects.

<u>HIE Use Depth</u>

Compared to HIE use that was not team-based, team-based HIE use was negatively related to HIE use depth in the two weeks prior to the visit ($ß_{-2wk}$=-4.2, p=0.014) as well as in the two weeks following the visit ($ß_{+2wk}$=-5.8, p<0.001, Figure 3.2, below). These results show that in the two weeks prior to the visit and the two weeks following the visit, team-based HIE use was associated with lower percentages (4.2 percentage points and 5.8 percentage points, respectively) of total HIE use spent on viewing specific documents. Team-based HIE use was unrelated to HIE use depth for HIE use occurring on the same day as the visit ($ß_{sameday}$=-2.7, p=0.076). Full results for this analysis are presented in Appendix B, Table B5.

Figure 3.2 Team-based HIE use and HIE use depth



Notes: HIE use depth is measured as the percentage of actions spent viewing specific documents. Models adjust for patient and visit characteristics as well as site and year fixed effects.

Discussion

Our findings illustrate that the majority of query-based HIE use in PCMHs is consistent with team-based models of care provision, and provides quantitative support for qualitative work documenting the importance of HIE in supporting team-based models of care [3.4,3.7,3.9,3.31,3.32]. More than 85% of use reflected team-based use, which demonstrates that query-based HIE use in our study sites is likely to support team-based care and facilitate better understanding of patient health context. While observational, our findings offer support for team-based health IT use as a potential mechanism that furthers our understanding of reductions in hospitalizations, utilization of specialty care and the emergency department, and primary care expenditures among PCMHs with more advanced health IT capabilities [3.33–3.36], despite variations in PCMH implementation [3.37]. Further research can build on the current study to examine the extent to which this mechanism, namely team-based use of HIE, is directly associated with better patient outcomes, higher provider satisfaction, and reduced burnout. Future studies should also consider the broader context of HIE tools available to the care team, given that HIE portal use is higher in the context of other forms of health information exchange [3.30].

In our analysis of the nature of team-based HIE use, we did not find that teams using HIE are more likely to look at more categories of clinical data (HIE use breadth), compared to non-team HIE use. This can be interpreted in a number of ways. On one hand, our findings are encouraging in that we do not find an information breadth gap (i.e. a significant negative relationship) between providers and teams using HIE. This supports the interpretation that delegated or team-based HIE is an exercise in task substitution across team members, and further bolsters the case for team-based use of HIE as a means to improve efficiency without sacrificing information gain in terms of breadth of information obtained from HIE systems. On the other hand, our findings are less encouraging in that we expect teams to consume more diverse information than providers alone due to fewer time constraints and more users. Of note, we do find a positive relationship between the number of HIE users and HIE use breadth (see Appendix B, Table B4), implying that HIE use by more users tends to result in a greater number of clinical information categories viewed.

HIE use depth – or the relative time spent on specific documents rather than summary sections of the HIE portal – is lower for teams using HIE in the weeks preceding and following a primary care visit, compared to non-team HIE use. In practice, this finding translates to delegates and teams spending less of their time in the HIE looking at specific documents compared to visit providers, however this difference only manifests prior to and following the visit. This suggests that teams using HIE can meet their information needs largely by consuming summative sections of the HIE portal when preparing for and following up on visits. Rather than needing specific report information in the weeks leading up to and following visits, teams using HIE tend to spend more of their activity examining collated information. This finding is consistent with previous literature showing providers' greater tendency to access specific documents and reports, compared to other HIE users [3.13]. Furthermore, this finding fits generally with a model of visit provider use of HIE to explore a specific past visit or laboratory result, for example, rather than perusing the HIE for a higher-level overview of patient data. Finally, in both breadth and depth of HIE use, we find significant heterogeneity across our study sites. This suggests that the well-documented variation in PCMH implementations - especially with respect to health IT capabilities [3.9,3.31,3.33] - may extend beyond adoption and into actual system use.

Our findings have a number of implications for organizations working to implement primary care delivery reform. First, our results suggest that query-based HIE is likely to be used in a team-based manner when deployed in PCMH settings, indicating that this form of HIE has a role to play in supporting team-based primary care delivery models. In particular, organizations implementing team-based information retrieval processes with HIE can expect for there to be no gap in the breadth of information consumed by the team, when compared to HIE use solely by the visit provider. Our results also have important implications for HIE system design and implementation in the context of primary care, as we see that HIE use among teams tends to involve more summative, collated data than HIE use by visit providers in the weeks preceding and following a visit. This finding suggests that query-based HIE system designers should emphasize easy access to and use of detailed report information for visit providers. For example, this may take the form of role- and access-time based workflows for visit providers that ease their access to individual-level reports, as these users are more likely to prioritize more detailed information.

Conclusion

We linked log data from a query-based HIE portal with clinical EHR data from three PCMH-recognized FQHCs to first estimate the prevalence of team-based HIE use in primary care. Second, we used multivariate regression models to analyze the relationship between team-based HIE use and the breadth and depth of that use, compared to HIE use that did not involve a team. We found that the vast majority of HIE use was team-based, however team-based HIE use was not related to HIE use breadth. Team-based use was correlated with less deep use in the weeks before and after a visit. Taken together, our findings support the role of HIE in primary care delivery redesign, specifically in supporting task delegation and team-based HIE workflows. Furthermore, we find no evidence of information gaps between visit providers and teams using HIE, and find that teams prioritize summative information in the HIE over exploration of specific results and reports.

References

3.1 Creating Patient-centered Team-based Primary Care | PCMH Resource Center. https://pcmh.ahrq.gov/page/creating-patient-centered-team-based-primary-care (accessed 27 Feb 2020).

3.2 Rittenhouse DR, Shortell SM, Fisher ES. Primary care and accountable care—two essential elements of delivery-system reform. N Engl J Med 2009;361:2301–3.http://www.nejm.org/doi/full/10.1056/NEJMp0909327

3.3 Leventhal T, Taliaferro JP, Wong K, et al. The patient-centered medical home and health information technology. Telemed J E Health 2012;18:145–9. doi:10.1089/tmj.2011.0130

3.4 Richardson JE, Vest JR, Green CM, et al. A needs assessment of health information technology for improving care coordination in three leading patient-centered medical homes. J Am Med Inform Assoc 2015;22:815–20. doi:10.1093/jamia/ocu039

3.5 King J, Patel V, Jamoom E, et al. The role of health IT and delivery system reform in facilitating advanced care delivery. Am J Manag Care 2016;22:258–65.https://www.ncbi.nlm.nih.gov/pubmed/27143291

3.6 Heisey-Grove D, Patel V. National findings regarding health IT use and participation in health care delivery reform programs among office-based physicians. J Am Med Inform Assoc 2017;24:130–9. doi:10.1093/jamia/ocw065

3.7 Wagner EH, Flinter M, Hsu C, et al. Effective team-based primary care: observations from innovative practices. BMC Fam Pract 2017;18:13. doi:10.1186/s12875-017-0590-8

3.8 Adler-Milstein J, Cohen GR. Implementing the IT infrastructure for health reform: adoption of health IT among patient-centered medical home practices. AMIA Annu Symp Proc 2013;2013:11–6.https://www.ncbi.nlm.nih.gov/pubmed/24551318

3.9 Bitton A, Schwartz GR, Stewart EE, et al. Off the Hamster Wheel? Qualitative Evaluation of a Payment-Linked Patient-Centered Medical Home (PCMH) Pilot. Milbank Q 2012;90:484–515.https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-0009.2012.00672.x

3.10 Kim KK, Rudin RS, Wilson MD. Health information technology adoption in California community health centers. Am J Manag Care 2015;21:e677–83.https://www.ncbi.nlm.nih.gov/pubmed/26760431

3.11 Unertl KM, Johnson KB, Lorenzi NM. Health information exchange technology on the front lines of healthcare: workflow factors and patterns of use. J Am Med Inform Assoc 2012;19:392–400. doi:10.1136/amiajnl-2011-000432

3.12 Wagner EH, Gupta R, Coleman K. Practice transformation in the safety net medical home initiative: a qualitative look. Med Care 2014;52:S18–22. doi:10.1097/MLR.0000000000000196

3.13 Vest JR, Grinspan ZM, Kern LM, et al. Using a health information exchange system for imaging information: patterns and predictors. AMIA Annu Symp Proc 2013;2013:1402–11.https://www.ncbi.nlm.nih.gov/pubmed/24551416

3.14 Cross DA, McCullough JS, Banaszak-Holl J, et al. Health information exchange between hospital and skilled nursing facilities not associated with lower

readmissions. Health Serv Res Published Online First: 10 October 2019. doi:10.1111/1475-6773.13210
3.15 Ben-Assuli O, Shabtai I, Leshno M. The impact of EHR and HIE on reducing avoidable admissions: controlling main differential diagnoses. BMC Med Inform Decis Mak 2013;13:49. doi:10.1186/1472-6947-13-49
3.16 American College of Physicians, Smith CD, Balatbat C, et al. Implementing Optimal Team-Based Care to Reduce Clinician Burnout. NAM Perspectives 2018;8. doi:10.31478/201809c
3.17 Richardson JE, Kern LM, Silver M, et al. Physician Satisfaction in Practices That Transformed Into Patient-Centered Medical Homes: A Statewide Study in New York. Am J Med Qual 2016;31:331–6. doi:10.1177/1062860615581654
3.18 HRSA. Federally Qualified Health Centers. Official web site of the U.S. Health Resources & Services Administration. https://www.hrsa.gov/opa/eligibility-and-registration/health-centers/fqhc/index.html (accessed 22 Nov 2019).
3.19 Rochester Regional Health Information Organization. About Us. Rochester RHIO. https://rochesterrhio.org/AboutUs (accessed 22 Nov 2019).
3.20 Goodman RA, Posner SF, Huang ES, et al. Defining and measuring chronic conditions: imperatives for research, policy, program, and practice. Prev Chronic Dis 2013;10:E66. doi:10.5888/pcd10.120239
3.21 Vest JR, Gamm LD, Ohsfeldt RL, et al. Factors associated with health information exchange system usage in a safety-net ambulatory care clinic setting. J Med Syst 2012;36:2455–61. doi:10.1007/s10916-011-9712-3
3.22 Cross DA. Electronic Information Sharing to Improve Post-Acute Care Transitions. 2018.https://deepblue.lib.umich.edu/handle/2027.42/146031
3.23 Politi L, Codish S, Sagy I, et al. Use patterns of health information exchange through a multidimensional lens: conceptual framework and empirical validation. J Biomed Inform 2014;52:212–21. doi:10.1016/j.jbi.2014.07.003
3.24 Vest JR, Kern LM, Campion TR Jr, et al. Association between use of a health information exchange system and hospital admissions. Appl Clin Inform 2014;5:219–31. doi:10.4338/ACI-2013-10-RA-0083
3.25 Vest JR, Zhao H, Jasperson J, et al. Factors motivating and affecting health information exchange usage. J Am Med Inform Assoc 2011;18:143–9. doi:10.1136/jamia.2010.004812
3.26 RStudio Team. R Studio. 2015. http://www.rstudio.com/
3.27 R Core Team. R: A Language and Environment for Statistical Computing. Vienna, Austria: : R Foundation for Statistical Computing 2018. https://www.R-project.org/
3.28 Wickham H. The tidyverse. R package ver 1 1 1 Published Online First: 2017.https://slides.nyhackr.org/presentations/The-Tidyverse_Hadley-Wickham.pdf
3.29 Dowle M, Srinivasan A. data.table: Extension of `data.frame`. 2019. https://CRAN.R-project.org/package=data.table
3.30 Vest JR, Unruh MA, Casalino LP, et al. The complementary nature of query-based and directed health information exchange in primary care practice. J Am Med Inform Assoc Published Online First: 8 October 2019. doi:10.1093/jamia/ocz134

3.31 Vest JR, Kern LM, Jung H-Y, et al. Patient-centered medical homes: observable types derived from national recognition assessment scores. J Ambul Care Manage 2015;38:144–52. doi:10.1097/JAC.0000000000000064
3.32 Morton S, Shih SC, Winther CH, et al. Health IT-Enabled Care Coordination: A National Survey of Patient-Centered Medical Home Clinicians. Ann Fam Med 2015;13:250–6. doi:10.1370/afm.1797
3.33 David G, Saynisch PA, Smith-McLallen A. The economics of patient-centered care. J Health Econ 2018;59:60–77. doi:10.1016/j.jhealeco.2018.02.012
3.34 David G, Gunnarsson C, Saynisch PA, et al. Do patient-centered medical homes reduce emergency department visits? Health Serv Res 2015;50:418–39. doi:10.1111/1475-6773.12218
3.35 Adler-Milstein J, Cohen GR, Markovitz A, et al. The Impact of HIT on Cost and Quality in Patient-Centered Medical Home Practices. AMIA Annu Symp Proc 2014;2014:232–9.https://www.ncbi.nlm.nih.gov/pubmed/25954324
3.36 Kern LM, Edwards A, Kaushal R. The Patient-Centered Medical Home and Associations With Health Care Quality and Utilization: A 5-Year Cohort Study. Ann Intern Med 2016;164:395–405. doi:10.7326/M14-2633
3.37 Tirodkar MA, Morton S, Whiting T, et al. There's more than one way to build a medical home. Am J Manag Care 2014;20:e582–9.https://www.ncbi.nlm.nih.gov/pubmed/25741875
3.38 Vest JR, Unruh MA, Shapiro JS, et al. The associations between query-based and directed health information exchange with potentially avoidable use of health care services. Health Serv Res Published Online First: 21 May 2019. doi:10.1111/1475-6773.13169
3.39 Rochester Regional Health Information Organization. Data Sources. Rochester RHIO. https://rochesterrhio.org/DataSources (accessed 22 Nov 2019).
3.40 Vest JR, Kern LM, Silver MD, et al. The potential for community-based health information exchange systems to reduce hospital readmissions. J Am Med Inform Assoc 2015;22:435–42. doi:10.1136/amiajnl-2014-002760
3.41 Campion TR Jr, Edwards AM, Johnson SB, et al. Health information exchange system usage patterns in three communities: practice sites, users, patients, and data. Int J Med Inform 2013;82:810–20. doi:10.1016/j.ijmedinf.2013.05.001

Chapter 4: User-level patterns of HIE use

Introduction

Widespread interoperable health information exchange (HIE) has the potential to provide more complete information to clinicians, improve care coordination and patient health outcomes, and reduce costs [4.1–4.3]. Efforts to realize these benefits have been encouraged by the HITECH Act's multi-billion-dollar investment in the underlying infrastructure of health information technology (IT) [4.4,4.5] and ongoing federal efforts to incentivize HIE implementation [4.6]. However, beyond organizational adoption and implementation, care team members must use these technologies if these system-wide benefits are to be achieved [4.7,4.8]. Despite over half of office-based physicians reporting access to these tools [4.9,4.10], query-based HIE use is reported in less than 10 percent of visits [4.11–4.14]. These estimates are generally understood to reflect lower than optimal usage [4.12], even when considering that not all visits require HIE, optimal usage rates are unknown, and these optimal rates likely vary by setting, provider type, and patient characteristics. In order to effectively apply health IT to propel the US health care system towards ambitious quality goals and cost-savings [4.15,4.16], targeted attention to how providers are - and are not - using HIE is warranted. Developing this evidence base on HIE system use is critical to informing system design towards higher usability, more efficient tools [4.7], as well as training approaches that foster long-term, regular system use.

To understand the nature of HIE use, an active body of research has leveraged HIE log files to identify variations in HIE use patterns along a number of dimensions. Scholars have characterized use sessions by frequency [4.11,4.17–4.19], duration [4.20], diversity of information accessed [4.21–4.25], timing of access relative to patient visit [4.7,4.26], navigation sequences [4.7,4.20,4.24,4.27,4.28], and use of different features [4.11,4.17]. Some of these studies have also abstracted granular measures into meaningful groupings, assigning use pattern labels such as “no use,” “basic use,” “advanced use,” “novel use,” “demographic use,” “clinical use,” “repeated search,” and “mixed use” [4.11,4.17,4.18,4.21,4.24,4.29] either using heuristics, theory, or empirical approaches like cluster analysis [4.7,4.24]. These definitions are subsequently used to stratify sessions of system use across roles, clinical settings, timing of use relative to the visit [4.24], and patient comorbidity factors [4.11,4.17]. Studies have shown that more advanced HIE use (e.g. duration or variety of information accessed) occurs more frequently than basic use for more complex patients [4.11,4.17], and retrospective and encounter-based usage are both more likely for patients with chronic diseases and recent ED visits [4.18]. Furthermore, HIE use patterns have been tied to clinical decision-making, primarily in that more advanced use is associated with lower likelihood of hospital admission in emergency encounters [4.17,4.30]. Lab and imaging ordering, another utilization measure, also decreased among hospital departments with “extensive” use of a HIE system [4.21]. Finally, a recent dissertation evaluated HIE use patterns and their relationship to readmission rates, finding that in post-acute care transitions, patients for whom only basic information was viewed had higher 30-day readmission rates [4.29].

Taken together, this literature demonstrates that methods of measuring and classifying HIE use patterns via log files are well-established, and have been incorporated into studies examining factors associated with patterns of use. While patient and setting factors are certainly important to study in relation to use patterns, user factors beyond role are also of importance. Because use measures are often calculated at the session level, research has focused on classifying sessions into categories, rather than examining how HIE users may demonstrate different patterns of use. User-level analyses commonly cite system rejectors and under-utilizers [4.31,4.32], behavior that can be rooted in system design issues, implementation challenges, or both. Zheng, et al. have used group-based modeling approaches to extend our understanding of health IT users by classifying health IT users into “use trajectories” over time [4.33–4.35], but the HIE use literature is sparse with respect to understanding of user-level variation in use patterns [4.24]. We are aware of no studies, for example, that measure patterns of HIE system use explicitly at the user level to differentiate categories of users, quantify the amount of system rejection or under-use, or analyze variation in use measures across user categories.

The purpose of this study is to measure, classify, and analyze user-level patterns of HIE system use. We apply and extend a conceptual model of multidimensional measurement of HIE use patterns to derive measures of HIE use at the session and user level for analysis [4.7]. Our study posits two research questions. First, how do users of an HIE system differ in measures of HIE use? Second, what are the differences in the relationships between use measures among “average” (i.e. non-outlier) users? Using system log data from a query-based HIE in New York state, we calculate 16 measures of HIE use across seven attributes. We then apply a cluster analysis to identify discrete groups of users according to aggregated session use measures, and identify high-frequency outlier users (“super users”), system rejectors, and under-users at the cluster level. We then further analyze differences in use measures and the relationships between use measures among users who do not demonstrate these characteristics, as little is known about variation that may exist within this commonly homogenized group of users. This treatment may mask important differences in use patterns among "typical" users that can help to refine HIE system design towards greater usability.

Improved system usability is key to realizing the purported benefits of health IT broadly and interoperable HIE systems in particular. For example, a system in which information retrieval workflows are highly inefficient is unlikely to have an impact on clinical decision-making and downstream outcomes. More vexing to system designers, different users may have different definitions for "efficiency" in information retrieval tasks. For example, one user may consistently need fast access to summative information, while another has a penchant for more detailed results review, as radiologists have in previous research [4.14]. Another comparison can be made with respect to how users vary in their use of time within the system; some may use longer duration sessions to examine less detail across several patients, while others may use the same duration of session to examine one patient in more depth. In the former case, usability hinges on patient search functionality and rapid chart retrieval, while the latter relies on within-chart navigability. In any case, some degree of variation will be due to role, setting, and patient-level factors, and some amount of within-user variation undoubtedly will exist, but HIE systems are less equipped to anticipate and respond to setting or session-level factors in the same way that they can observe user-level behavior and construct user-level navigation profiles accordingly. Currently, most HIE systems offer one-size-fits-all interfaces and workflows that may be ineffective for some users [4.19,4.36]. By identifying discrete groups of users who differ in their use patterns, system designers can more aptly accommodate this variation into workflows within the HIE system. This, in turn, may improve satisfaction with the tool and drive sustained use [4.37]. In particular, variation across “typical” users may disaggregate this group into distinct user types with different use measures that may fit different user profiles. User-level information can also be used to understand barriers that may be influencing lower use among users who are otherwise similar, and inform training or system design to reduce those barriers and facilitate use. Finally, understanding the nature of routine use among “typical” users (as opposed to that of “super users” or “non-users”) may be more informative in attenuating the learning curve for new or less advanced “typical” users, reduce their system rejection rates, and speed the time between early, less efficient use to routine use.

Materials and Methods

Setting

The Rochester Regional Health Information Organization (RHIO) operates in a 13-county region of western upstate New York, and has provided HIE services to health care providers and patients in the region since 2006 [4.38]. As of spring 2008, approved physicians and other health care providers could use a web-based portal to access patient health information contributed from health organizations in the area [4.38,4.39]. Contributing organizations - including hospitals, laboratories, physician practices, public health agencies, home health centers, and payers - provide data to the Rochester RHIO database primarily via electronically exchanged Consolidated Clinical Data Architecture (C-CDA) documents [4.40,4.41]. Health information available in the database includes discharge summary documents, diagnoses, radiology reports and images, medication history, and laboratory results [4.13,4.14,4.40,4.42]. Currently, more than 1.4 million patients have data stored in the Rochester RHIO clinical database [4.38], which includes data from more than two hundred data-contributing organizations [4.40]. Between 2012 and 2016, the time of the data for this study, two-thirds of the hospitals and physician practices in the region participated in the exchange [4.14,4.42].

Users of the web-based HIE portal follow a common workflow immediately upon login. First, users search for a patient and, upon identifying the correct patient, confirm that the patient has opted-in to allow their data to be shared with clinicians via the exchange. Despite the opt-in model, Rochester RHIO generally reports that more than 97 percent of patients consent to exchange [4.38]. Once consent is confirmed, the user is directed to a landing page with a summary of the patient's most recent visit [4.43]. For all portal users, the session usage workflow up to this point is identical. After this point, users may pursue a number of use patterns. Users might navigate to other sections of the portal to find detailed information on the patient like medication history, laboratory data, or radiology reports. To view radiology images, users must first view the narrative reports. A second potential workflow could be to conclude the session of viewing that patient's record and search for another patient. In this case, users are directed back to the initial search page to query. Users are only able to access a single patient record at a time [4.13].

Users in our study are health care providers in three Rochester, New York-area FQHCs: Anthony Jordan Health Center (AJHC), Oak Orchard Community Health Center (OOCHC), and the Regional Primary Care Network (RCPN), a network of health centers with more than 20 service locations. FQHCs provide primary care services along with integrated dental and behavioral care to underserved areas in the US, and receive funding from the Health Resources and Services Administration (HRSA) [4.44]. The users in this study have various professional roles, as any approved care provider can access the Rochester RHIO query portal for patient information. Specifically, the following user roles appear in the HIE use log data: staff, care manager, mid-level clinician (e.g. physician assistants), midwife or registered nurse, nurse practitioner, licensed health professional (e.g. clinical social worker), and physician.

Data and Sample

Rochester RHIO log data contains all query portal use from users at the three FQHCs during the three years from January 2012 through December 2014. Actions taken in the query portal (i.e. clicks) are recorded as "events," and identify the portal page the user was on at the time of the activity, including pages associated with logging in and searching for patient records, which occur outside the context of a patient chart. Within single patient charts, the use log records events for navigation to specific areas of the patient record, which allows for identification of the types of clinical information accessed during the user's session (e.g. summary information and/or laboratory results). User identifiers were linked to a list of registered HIE portal users, which provided the user role category. User log data also includes event timestamps measured to the millisecond and a patient identifier for user activity that occurred within a patient record. For example, while login events are recorded, none are associated with patient identifiers because login occurs before the user queries for a patient.

The user log data does not begin at the time of system implementation, so we applied a washout period to isolate users' initial experiences with the query portal. We excluded all activity from users appearing within three months of the start of the user log data, January 2012. This exclusion resulted in an analytic dataset including 172 unique users with 9,958 use sessions. HIE use sessions are defined by gaps in user activity lasting longer than 20 minutes. If a user's most recent action occurred more than 20 minutes in the past, the next action constituted the beginning of a new session. The 20-minute cutoff is based on the automatic time-out for portal of 20 minutes, and aligns with other cutoff-time definitions of HIE use sessions in health services research [4.26].

Conceptual Framework: Multidimensional Use Patterns of HIE

To inform our measures of HIE use, we applied a conceptual framework by Politi, et al. specific to characterizing HIE use sessions using log files by measuring use across multiple dimensions [4.7]. Applying a consistent measurement framework facilitates cross-study comparisons and allows researchers to isolate the specific aspect or nature of use that may improve user satisfaction and be instrumental in furthering our understanding of how providers should use these tools to impact cost and quality of care [4.31,4.45]. Furthermore, consistent measures of use can better inform practice guidelines regarding workflow recommendations and the types of system use that yield the most value [4.46].

The Politi, et al. framework posits five use "attributes" measured at the session level: volume, diversity, granularity, duration of screen display, and content. The measurement framework is depicted in Appendix C, Figure C1. Volume in this model refers to the amount of information involved in a use session, typically measured by total number of screen views [4.24]. This measure has also been termed "intensity" in previous work using log data to describe patterns of use in HIE systems [4.29]. Diversity refers to the different types of information accessed in a given use session, and is commonly measured as the count of discrete information categories viewed in a session [4.24,4.47, 4.48]. Granularity further specifies the nature of the information viewed during the session, and explicitly accounts for the fact that information in an HIE system can vary in its specificity from summative screens to specific result documents. Measuring this attribute requires user log data capturing the hierarchical aspects of information viewing, and can be operationalized as the highest level of specificity or counts of screen views for each level of specificity in the hierarchy [4.47]. Duration of screen display captures the amount of time a user spent viewing information during the session. This attribute has also been operationalized as total session duration [4.47], and in their validation of the framework, Politi, et al. operationalize this measure at the session level as the median number of seconds spent on each page (i.e. between actions) [4.7]. Finally, content further specifies the actual clinical information types (e.g. laboratory or radiology) viewed during a session. This measure can be operationalized as binary indicators for each clinical information category or counts of page views for each clinical information category [4.47,4.49].

The current study extends this framework to include two additional attributes: one session level attribute and one user level attribute. At the session level, we include efficiency, which captures the amount of activity in a given session that is not directly related to viewing clinical information about a patient. Because clinical information retrieval is the primary task of HIE use [4.19,4.36], we propose this attribute as a measure of session level barriers to successful retrieval of information. These barriers could come in the form of failed login attempts, failed patient searches, or other actions that take place in the HIE system but do not take place in the context of a specific patient record. In the context of EHR audit logs, this attribute has been operationalized as time spent on navigation activities [4.50]. In an HIE context, this attribute could also be operationalized as the proportion of either total session time or actions occurring outside of a patient record.

Finally, we extend the framework to include user participation, a user-level attribute capturing measures of users' HIE system use that extend across sessions. This attribute measures variation in the frequency, regularity, or concentration of system use [4.36]. Furthermore, this attribute is tied to the voluntariness of system use, a primary construct of theories of technology adoption and use [4.51]. For example, individuals in a primary care practice who are tasked with coordinating care with outside providers would likely need to use HIE systems frequently to complete these tasks, compared to clinical team members that may have relatively fewer tasks that necessitate the use of the HIE. As a result, participation measures for these individuals would differentiate them from other users whereas their session-level use may look similar to other users for whom HIE use was more voluntary.

Operationalization of Session & User Attributes: Measures of HIE Use

We constructed HIE use measures for each of the five conceptual framework attributes and our two additional attributes. For use volume, we measured both the number of discrete actions a user took during the session and the number of unique patients whose charts were viewed during the session. For diversity, we measured the count of discrete information categories viewed during a session. We separated "information categories" by both clinical data domain and document type. For example, an action on a laboratory summary page and an action to open a laboratory result document would count as two information categories, as the result report provides context and information not available on the summary page. To measure granularity, we measured the proportion of all clinical actions spent viewing specific result reports pages, such that higher proportions indicated more granular use. For duration, we measured the total session duration in minutes as the difference between the first and last session actions. To measure content, we constructed counts of actions for each of the following clinical information content domains: summary pages, laboratory pages (including individual result reports), radiology pages (including result reports), vitals pages (including result reports), and admission, discharge, and transfer pages, also including actions indicating viewing of specific ADT documents.

Our framework attribute extensions were measured in three ways each. For efficiency, we calculated the proportion of actions in a given session that occurred outside of a patient chart. These largely consisted of login and patient search actions. We also calculated the proportion of these outside-chart actions for logins and searching, respectively. The first measure captures time spent "getting to" clinical data in the HIE, relative to time spent viewing clinical data within a patient record, while the other two further delineate the nature of these outside-chart actions. For analysis, we aggregated all session use measures above to averages at the user level.

Finally, to measure user-level participation, we constructed measures for total number of sessions per observed user lifespan days (defined as days between a users' first and last session in the data), number of sessions per active use day (count of days during which the HIE was used), and the median number of days between active days of HIE use. We use these measures for two reasons. First, each captures a different dimension of the user participation attribute. Total sessions per observed lifespan day captures a measure of use frequency, while number of sessions per active use day captures a measure of use concentration, which may differentiate ad-hoc users from those who concentrate use on a single work day. Days between active use days accounts for regularity of use, insofar as some users may reliably use a system once per week, while others may have more sporadic use. Second, the two ratio measures account for the limitation that we cannot be sure that we observe a users' final use session, given that the data is a snapshot of use between 2012 and 2015, with unobserved use occurring both before and after our data. This prevents us from measuring true user "lifespan" or having comparable measures of total number of use sessions. A mapping of the framework attributes to our use measures can be found in Table 4.1.

Table 4.1 Framework attributes and measure operationalization

Framework Attribute	Measure(s)
Volume	• Count of discrete actions • Count of unique patients whose charts were viewed
Diversity	• Count of discrete information categories viewed
Granularity	• Proportion of clinical actions viewing specific result reports (higher proportions indicate more granularity)
Duration of Screen Display	• Total session duration in minutes
Content	• Count of actions on: o Summary pages o Laboratory pages, including documents o Radiology pages, including documents o Vitals pages, including documents o Admission, Discharge, Transfer screens, including documents
Efficiency*	• Proportion of actions outside a patient chart • Proportion of outside-chart actions attributable to login actions • Proportion of outside-chart actions attributable to patient search actions
Participation (user-level)*	• Sessions per active use day • Sessions per user "lifespan" day • Median number of days between active use days

Notes: *Efficiency and Participation attributes are extensions of the Politi, et al. conceptual framework of multidimensional use of HIE. Further detail on definitions of Volume, Diversity, Granularity, Duration, & Content attributes can be found in [7].

Classifying Users: Clustering Algorithm

To identify patterns of aggregate use at the user level, we applied a Clustering Large Applications (CLARA) clustering algorithm to the user-level aggregate HIE use measures, similar to the Politi, et al. conceptual framework validation of session-level use measures [4.7,4.52]. While our user log data did not constitute a high-dimensional dataset, the Euclidean distance calculations in the k-medoids partitioning algorithm, referred to as partitioning around medoids (PAM), allow for missing values in the data, which is a key weakness in traditional k-means cluster analysis approaches. In our case, users demonstrating only one day of active HIE use had no measure of days between active use days. Excluding these users from the cluster analysis would have yielded biased clusters that neglected these single-day HIE users.

In cluster analysis, one must pre-specify the number of clusters in the data, which requires determining the number of clusters that optimizes model fit by reducing bias without overfitting the data and introducing extraneous variation, as can occur in prediction models [4.53]. We applied CLARA clustering with values of k ranging from 1 to 10 and used the weighted sum of squares (WSS) as a measure of model fit. Visual examination of the WSS statistic in the form of a "scree plot" is a common method for identifying the optimal number of clusters, which is the value of k at which additional clusters did not reduce the WSS error meaningfully [4.54]. This is referred to as the "elbow" of the scree plot, and is visually evaluated at the value of k at which the slope of the WSS curve flattens (Appendix C, Figure C2). We ran the clustering algorithm with 1000 randomly selected samples for model stability. This divided the users into five discrete clusters using the 16 continuous user-level measures of HIE use described above and summarized in Table 4.1. We present user cluster means resulting from the cluster analysis and describe cluster differences across attributes.

Secondary Analyses: MANOVA Test for Differences in Non-Outlier Clusters

After identifying and describing the differences between user clusters, we labeled clusters based on the primary differences in use measures between clusters. We then identified outlier user clusters as those that demonstrated measures consistent with "super user" HIE use and those that demonstrated very low system use. While it is clear that cluster analysis would yield statistically different groups of users, it is not guaranteed that all user groups would differ from all other groups in statistically significant ways. We sought to analyze differences across non-outlier user groups only; thus, outlier user clusters were excluded from our secondary analysis. This allowed us to focus on session-level use measures that differed across these "average" user groups. We used a multivariate analysis of variance (MANOVA) test to analyze the joint and individual association between our session use measures as dependent variables and the user group derived from the cluster analysis as the independent variable along with user role and an interaction term between the user group and role. This approach allowed for flexibility with respect to the results of the cluster analysis in the first stage of analysis, as MANOVA is designed for analysis of multiple dependent variables and can accommodate any number of groups as an independent variable. Due primarily to the presence of unequal sample sizes in this analysis and lack of homogeneity of covariance matrices across groups, we report the Pillai test statistic, which is a more conservative measure of joint significance. We used a significance cutoff of $p<0.05$ in our primary model. In post-hoc univariate tests, we used a Bonferroni-adjusted cutoff of $p<0.00417$ to correct for multiple comparisons and for a more conservative measure of significance in the presence of heterogeneous variance across user groups. User participation measures were excluded from our secondary analysis, as those measures can only be calculated at the user level. Furthermore, due to high correlation with other use measures, we excluded the volume measure of number of actions in the session.

HIE Use Measure Correlation Differences Across User Groups

To further address our second research question, we analyzed differences in the relationships between HIE use variables across non-outlier user groups. We computed Pearson correlation coefficient matrices for all HIE use measures for each user group included in the MANOVA. We identified significant use measure correlations as those with an absolute value above 0.6 and a p-value less than 0.05. Then, for correlations that were statistically significant in all groups, we computed the absolute difference in the correlation value between user groups to identify candidate correlations with potential significant differences across the user groups. Our cutoff for candidate correlations was an absolute group difference of at least 0.25. This allowed us to identify the correlations with the highest magnitude differences across user groups. Finally, we tested the correlations for differences in the correlation value across groups using Fisher's z-test, to identify the HIE use measure relationships that differed across user groups [4.55].

All data preparation, computation of HIE use measures, and analysis were done in the RStudio development environment [4.56] using the R statistical programming language [4.57]. The tidyverse suite of packages was the primary software library used to construct the analytical data file, in addition to data.table [4.58, 4.59]. The cocor, stats, cluster, and rstatix packages were used for analysis [4.55,4.57,4.60,4.61]. This study was approved by the Indiana University Institutional Review Board.

Limitations

Our study has several limitations. First, we observe a relatively small sample of primary care users in a single region of the US which may not generalize to other regions or care settings. Clinical care environments other than FQHCs may demonstrate different

HIE use patterns based on varying information needs, scheduling practices, and visit acuity. Second, we only observe use of one regional, query-based HIE portal. Query-based HIE use has demonstrated a complementary relationship with directed HIE [4.13], but our analysis does not include measures of directed HIE use. As a result, we may observe measures of query-based HIE use that are not independent from changes in directed HIE use during the study period. For example, users may decrease use of query-based HIE if directed HIE at their site dramatically improves, which would appear in our measures as low HIE participation among users but would lack important context. Furthermore, the log data underpinning our use measures and analysis is a sample of use data from a period in time, both before and after which users continued to use the HIE. We attempt to identify early use among all users via a three-month washout period at the beginning of our data, however it is unlikely that the last observed session is truly that user's last session, especially among longer-term users and those whose first use session was near the end of the study data. To address this, our participation measures are normalized over the course of a user's observed lifespan days and active HIE use days. Finally, we do not estimate causal relationships or causal mechanisms driving the observed clusters of HIE use patterns or use differences across non-outlier user clusters. By design, this study is descriptive in nature and aims only to describe these differences rather than identify any of the mechanisms underpinning those differences.

Results

The final analytic sample of users and sessions included 172 distinct users across 9,958 use sessions. Overall, users had a median of 8 active use days of HIE, and averaged 1.3 use sessions per active use day (sd=0.4 sessions). The average number of actions in a session was 19.6 (sd=18.0 actions), and on average sessions lasted 5.3 minutes (sd=6.6 minutes). Users accessed 2 different information categories, on average (sd=1.5 categories), and had the most activity on summary pages (4.6 actions per session, on average, sd=6.0). Less activity was observed with respect to laboratory content (0.9 actions per session), vitals content (0.8 actions per session), radiology content (0.3 actions per session), and ADT content (0.2 actions per session).

User Level Aggregate Use Patterns

In the user-level cluster analysis of aggregate use measures, the best-fit model was achieved with k=5 clusters of users (Appendix C, Figure C2). We described the clusters according to the use measure averages that most differentiated the cluster from other clusters, and developed shorthand names for the clusters for purposes of discussion. The largest cluster (n=63) we labeled "Regulars" (Table 4.2). These users demonstrated moderate volume measures (27.1 actions and 0.9 patients viewed per session, on average) and the most efficient use (59.4% of activity outside the patient record, 14.1% of that activity spent on login activities), relative to other users. These users also had the second-highest diversity measures, with an average of 3.4 information categories viewed per session. Regulars illustrated moderate granularity, spending an average of 12.5% of their within-chart actions on viewing specific results, as opposed to on summary sections of the HIE. In terms of participation, Regulars averaged 1.5 use sessions on active use days. Finally, Regulars had the second-longest duration sessions on average at 6.2 minutes.

Table 4.2 Cluster analysis results of user-level aggregate HIE use measures

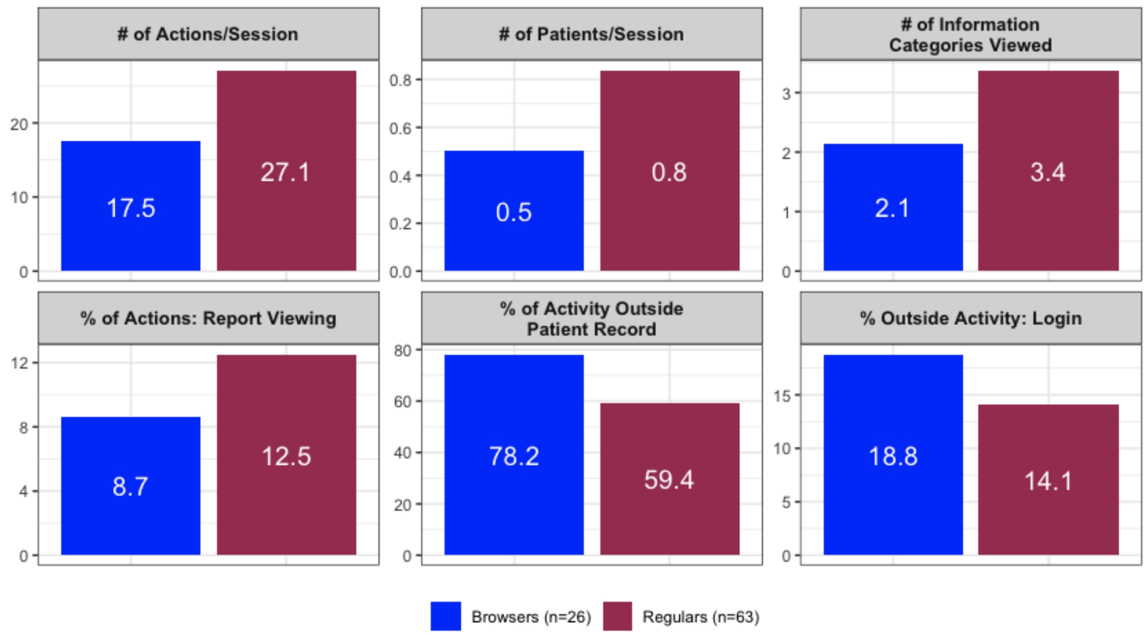
		CLARA Clustering Results: User Group Cluster Centroids *Mean (sd) values of user-level measures used in cluster analysis*					
		Overall	Low Volume, Inefficient *Quitters*	Low Volume, Inefficient *Attemptors*	Moderate Volume, Less Efficient *Browsers*	Moderate Volume, Efficient *Regulars*	High Volume, Long Duration *Superusers*
	# of Users	172	31	47	26	63	5
	# of Sessions	9,958	59	298	1,055	7,870	676
Attribute	***Use Measure***						
User Participation	# of Sessions per Active Use Day	1.3 (0.4)	1.1 (0.3)	1.1 (0.2)	1.3 (0.2)	1.5 (0.4)	2.1 (1.1)
User Participation	Median Days btw Active Use Days	29.3 (73.4)	52.5 (86.6)	89.2 (125.6)	7.5 (7.5)	5.9 (7.7)	5.4 (5.0)
User Participation	# of Sessions per Lifespan Day	0.5 (0.5)	0.9 (0.5)	0.5 (0.6)	0.2 (0.1)	0.3 (0.4)	0.8 (1.1)
Volume	# of Actions per Session	19.6 (18.0)	4.4 (2.6)	12.1 (8.0)	17.5 (4.7)	27.1 (6.0)	100.9 (26.4)
Volume	# of Patients per Session	0.6 (0.8)	0.0 (0.0)	0.2 (0.4)	0.5 (0.2)	0.9 (0.4)	4.6 (0.7)
Diversity	# of Information Categories Viewed	2.0 (1.5)	0.3 (0.4)	1.1 (0.9)	2.1 (0.5)	3.4 (0.8)	4.1 (1.9)
Granularity	Proportion of Clinical Actions on Reports	14.1 (21.8)	0.0 (0.0)	22.6 (35.1)	8.7 (7.8)	12.5 (9.2)	22.6 (37.2)
Duration	Session Duration (mins)	5.3 (6.6)	2.5 (7.3)	3.6 (3.4)	4.7 (2.7)	6.2 (3.5)	32.5 (7.9)
Content	Summary Pages (count of actions)	4.6 (6.0)	0.0 (0.0)	0.6 (1.4)	4.3 (1.7)	8.3 (3.6)	25.4 (13.2)
Content	Lab Content (count of actions)	0.9 (1.6)	0.0 (0.0)	0.1 (0.3)	0.4 (0.4)	1.6 (1.1)	6.7 (5.4)
Content	Radiology Content (count of actions)	0.3 (0.6)	0.0 (0.0)	0.1 (0.2)	0.2 (0.2)	0.6 (0.5)	2.1 (2.4)
Content	Vitals Content (count of actions)	0.8 (3.2)	0.0 (0.0)	0.7 (1.8)	0.5 (0.8)	0.7 (1.2)	8.2 (17.2)
Content	ADT Content (count of actions)	0.2 (0.3)	0.0 (0.0)	0.0 (0.1)	0.1 (0.2)	0.3 (0.4)	0.2 (0.1)
Efficiency	% of Activity Outside Patient Record	78.9 (18.4)	100.0 (0.0)	93.2 (10.9)	78.2 (5.6)	59.4 (7.2)	64.8 (8.5)
Efficiency	% of Outside Activity: Login	23.8 (15.2)	49.6 (12.0)	23.9 (9.5)	18.8 (7.3)	14.1 (4.7)	10.2 (4.4)
Efficiency	% of Outside Activity: Patient Search	78.9 (18.4)	100.0 (0.0)	93.2 (10.9)	78.2 (5.6)	59.4 (7.2)	64.8 (8.5)
User Role n (%)	Care Manager	5 (2.9)	0 (0.0)	2 (4.3)	0 (0.0)	3 (4.8)	0 (0.0)
	Licensed Health Professional	51 (29.7)	13 (41.9)	6 (12.8)	9 (34.6)	23 (36.5)	0 (0.0)

Medical Doctor	13 (7.6)	3 (9.7)	5 (10.6)	1 (3.8)	4 (6.3)	0 (0.0)
Mid-Level	1 (0.6)	0 (0.0)	1 (2.1)	0 (0.0)	0 (0.0)	0 (0.0)
MIDWIFE/RN	1 (0.6)	0 (0.0)	0 (0.0)	0 (0.0)	1 (1.6)	0 (0.0)
Nurse Practitioner	9 (5.2)	3 (9.7)	3 (6.4)	1 (3.8)	2 (3.2)	0 (0.0)
Staff	30 (17.4)	3 (9.7)	4 (8.5)	6 (23.1)	14 (22.2)	3 (60.0)
Unknown	62 (36.0)	9 (29.0)	26 (55.3)	9 (34.6)	16 (25.4)	2 (40.0)

Notes: Values represent group averages with standard deviations in parentheses, unless otherwise noted.

Our second cluster of users we labeled "Browsers" (n=26), as they demonstrated moderate volume use that was less than Regulars and slightly less efficient, as well as less diverse. Browsers had cluster averages of 17.5 actions per session and 0.5 patient records viewed per session. Browsers had shorter duration sessions than Regulars (4.7 vs. 6.2 minutes), and viewed fewer information categories per session (2.1 categories). Browsers demonstrated lower efficiency than Regulars, spending an average of 78.2% of actions outside patient charts. In participation measures, Browsers averaged 1.3 use sessions on active use days, only slightly fewer than Regulars. Finally, in our measure of granularity, Browsers spent 8.7% of their within-chart actions on viewing specific results. We compare Browsers and Regulars in our secondary analysis, as these are the two clusters of "typical" users that did not demonstrate exceptionally low or exceptionally high system use (Figure 4.1). The remaining three clusters, described below, fit either "super user" or non-user use patterns, and thus were excluded from the secondary analysis.

Figure 4.1 Selected cluster mean differences of session use measures, Browsers and Regulars



Notes: All differences presented are statistically significant (p<0.01).

The second largest cluster (n=47) were termed "Attempters," as these users demonstrated shorter session durations, on average (3.6 minutes), low use volume (12.1 actions and 0.2 patients per session, on average), and very inefficient use (93.2% of actions spent outside patient records, with 23.9% of those actions spent on login activity, on average). Furthermore, users in this cluster had low use diversity, with an average of 1.1 information categories viewed per session. Counter to this, Attempters showed high levels of granularity with 22.6% of within-chart activity spent on viewing result reports, on average. Attempters had the lowest average number of sessions per active use day (1.1 sessions); this is in part due to many of these users having only one HIE use session on a single active use day.

While Attempters demonstrated low volume and relatively inefficient use, "Quitters" (n=31) had even lower volume and less efficient HIE use. The average session involved zero patients, only 4.4 actions, and registered 0.3 information categories viewed over a 2.5-minute duration. Consistent with inefficient use, Quitters had an average of 100% of activity spent outside the patient record, with 49.6% of this activity spent on login activities. Due in part to this inefficiency, Quitters had very low granularity measures on average (0.0%). Like Attempters, Quitters also had 1.1 sessions per active use days, largely as result of having a single use on a single day in the three years of the log data.

Finally, the smallest cluster of users was "Superusers" (n=5), who demonstrated exceptionally high volume and long duration use sessions. These five users had an average of 100.9 actions per session, over an average session duration of 32.5 minutes, viewing 4.1 information categories across 4.6 patient records. An average of 25.4 superuser actions per session were dedicated to summary pages, while 6.7 were dedicated to lab content, far outstripping all other cluster content measures. Superusers also illustrated high granularity use from Superusers, with 22.6% of actions within the chart on viewing specific results, a rate on par with Attempters, roughly three times that of Browsers, and almost twice that of Regulars. Superusers also had the highest average number of sessions per active use day, with 2.1 sessions per day of use. Finally, Superusers demonstrated efficient system use, with only 64.8% of activity spent outside patient records and only 10.2% of this activity spent on login activities.

Comparison of Regulars and Browsers: Session-Level Use Measures

Eighty-nine of the 172 users (51.7%) were either Regulars or Browsers, and as such met our criteria for inclusion in the secondary analysis comparing non-outlier HIE users. These users accounted for 8,925 of the 9,958 sessions in our sample (89.6%). Within these two groups, the HIE use measures were somewhat but not highly correlated (Appendix C, Tables C1 and C2), one of the conditions for use of MANOVA [4.62]. Our volume measure of number of actions per session was the measure most highly correlated with other use measures, and was excluded from this portion of the analysis. This left 12 HIE use measures representing all six use attributes as dependent variables. In the multivariate analysis, there was a significant difference between Browsers and Regulars in the linear composite of the dependent variables ($\eta^2_{group}=0.043$, $F(12, 7978)=29.64$, $p<0.001$) (Table 4.3). User role and the interaction between user group and role also indicated a significant relationship with the composite dependent variables ($\eta^2_{role}=0.271$, $F(72, 47838)=31.52$, $p<0.001$; $\eta^2_{group*role}=0.042$, $F(48, 31844)=7.07$, $p<0.001$). In univariate ANOVA comparisons across Browsers and Regulars, only the proportion of actions outside the chart spent on patient search (efficiency), number of actions examining vitals content (content) were not statistically different across these two user groups, using a Bonferroni-corrected $p<0.00417$ cutoff for significance (Table 4.3).

Table 4.3 MANOVA & Univariate ANOVA Results, differences in HIE use measures across Browsers and Regulars

DV: Linear Combination of HIE Use Measures

	DF	*Pillai*	*F-stat*	*p-value*
Group***	12, 7978	0.043	29.64	<0.001
User Role***	72, 47838	0.272	31.52	<0.001
Group*Role***	48, 31844	0.042	7.07	<0.001

ANOVA Univariate Comparisons

	Volume Measure		*Diversity Measure*		*Granularity Measure*		*Duration Measure*	
	# of Patients per Session***		***# of Information Categories Viewed******		***% of Clinical Actions on Results Viewing******		***Session Duration (mins)******	
	F-stat	*p-value*	*F-stat*	*p-value*	*F-stat*	*p-value*	*F-stat*	*p-value*
Group	60.41	<0.001	213.56	<0.001	66.56	<0.001	25.66	<0.001
User Role	64.82	<0.001	26.54	<0.001	26.65	<0.001	82.87	<0.001
Group*Role	9.00	<0.001	13.28	<0.001	5.03	<0.001	12.73	<0.001

Content Measures

	Summary Pages***		***Lab Content******		***Radiology Content******		***Vitals Content***		***ADT Content****	
	F-stat	*p-value*	*F-stat*	*p-value*	*F-stat*	*p-value*	*F-stat*	*p-value*	*F-stat*	*p-value*
Group	50.63	<0.001	79.53	<0.001	57.16	<0.001	0.1124	0.7375	8.58	0.0034
User Role	27.59	<0.001	7.59	<0.001	12.49	<0.001	7.60	<0.001	24.51	<0.001
Group*Role	2.24	0.063	1.07	0.370	3.92	0.0034	11.54	<0.001	4.68	0.0009

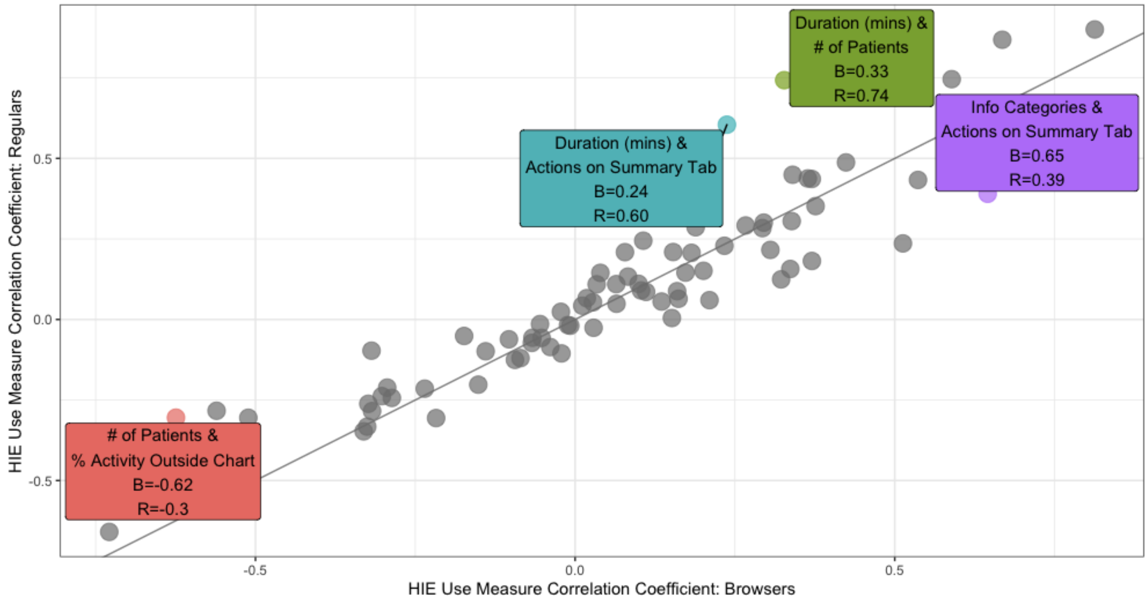
Efficiency Measures

	% of Activity Outside Patient Record***		***% of Outside Activity: Login******		***% of Outside Activity: Patient Search***	
	F-stat	*p-value*	*F-stat*	*p-value*	*F-stat*	*p-value*
Group	195.82	<0.001	108.48	<0.001	0.3173	0.5732
User Role	34.84	<0.001	51.53	<0.001	78.84	<0.001
Group*Role	1.47	0.208	0.4123	0.7999	12.16	<0.001

Notes: In ANOVA results, all comparisons for the Group independent variable have 1 degree of freedom. Role comparisons have DF=6, and Group*Role has DF=4. Due to high correlation with other HIE use variables, number of actions per session was excluded from the MANOVA and univariate ANOVA analyses. All significance indications are for association with the Group variable (Browsers or Regulars) and reflect a Bonferroni correction for multiple comparisons due to underlying heterogeneity in variance matrices across groups. The p-value used to estimate statistical significance was 0.05/12 tests = 0.00417. *$p < 0.05$ **$p<0.01$ ***$p<0.001$.

Four HIE use measure correlations coefficients demonstrated significant differences across Browsers and Regulars (Figure 4.2). Use volume and efficiency demonstrated a negative relationship in both groups, however the negative correlation between number of patients viewed per session and the proportion of activity taking place outside patient charts was stronger among Browsers than among Regulars ($\rho_{browsers}$= -0.62, $\rho_{regulars}$= -0.30). The correlation between volume (number of patients per session) and duration also differed across groups, with Regulars demonstrating a stronger positive correlation between these two measures ($\rho_{browsers}$= 0.33, $\rho_{regulars}$= 0.74). Duration also differed in its relationship with one content measure: number of actions on the summary tab of the HIE portal. Regulars demonstrated a stronger correlation in these two measures than Browsers ($\rho_{browsers}$= 0.24, $\rho_{regulars}$= 0.60). Finally, this content measure also varied across groups in terms of its relationship with use diversity (number of information categories viewed), this time with Browsers illustrating a stronger positive correlation than Regulars ($\rho_{browsers}$= 0.65, $\rho_{regulars}$= 0.39). All correlation coefficients are reported in Appendix C, Tables C1 and C2.

Figure 4.2 HIE use measure correlation difference between Browsers and Regulars



Notes: Each point represents two Pearson correlation coefficients between the same two HIE use variables, with the correlation among Browsers on the x-axis and Regulars on the y-axis. Highlighted correlations indicate those that differed in magnitude by over 0.25 between groups and at least one group had a statistically significant correlation coefficient of at least 0.6. Statistical significance of the difference between correlations was computed via Fisher's z-test. All highlighted correlation differences are statistically significant at the $p<0.001$ level.

Discussion

We analyzed HIE portal user data from 172 portal users at three FQHCs in New York state to identify discrete groups of users according to aggregate use patterns and to analyze differences in HIE use among non-outlier user clusters. We identified five user groups, differentiated in 16 measures across the use attributes of participation, volume, diversity, granularity, duration, content, and efficiency. Efficiency and volume of use were the primary attributes in which users differed, with very low-volume users (Attempters and Quitters) tending to have low efficiency use as well. The highest volume users (Superusers) had high efficiency measures as well as long session durations and high granularity use, consistent with the notion that more experience with a system will lead to improved efficiency as users develop routine navigation paths. Although we do not observe lack of use directly, the Attempters and Quitters groups offer insight into the prevalence of system under-use or disuse, and suggest that low efficiency measures may play a role in low observed utilization rates of these voluntary systems [4.2,4.13,4.63]. This finding fits with qualitative work that has emphasized barriers to HIE system access as a contributor to low provider adoption and use of HIE [4.63,4.64]. Furthermore, these findings support the inclusion of efficiency measures in HIE use measurement frameworks going forward. Efficiency measures such as these can also be utilized to measure the relative barriers to information access in terms of time, clicks, or proportion of session activity, which can in turn be used to compare implementations and system designs to identify more efficient systems or those that offer the most information access with the least administrative burden to users.

In comparing Browsers to Regulars, we found that these two groups did indeed differ across use attributes. This is predictable given that the user groups were identified via cluster analysis which seeks to maximize the distance between cluster centroids, however it was not guaranteed that these two most similar groups would differ. In fact, we found no significant difference in access to vitals content or in our efficiency measure of outside chart actions attributable to patient search actions. However, in aggregate, Regulars demonstrated greater rates of participation, use volume, diversity of information accessed, granularity of use, viewing of summary content, and other measures of efficiency, again supporting the theory that more system use begets greater efficiency. These results suggest two distinct tiers of non-outlier HIE users, those that use the system more regularly and those who do not. Importantly, these two groups cross-cut observed user roles, such that the user group was not perfectly predicted by a user's role. This suggests that historical HIE system use behavior may help to distinguish user groups in a way that role-based classification systems cannot. Rather than designing user "profiles" based on user role alone (e.g. a nurse or physician profile), HIE systems may better serve users by observing past behavior and customizing any dynamic elements of the system interface based on these historical use patterns. For example, a user profile for "Regulars" might include features that allow for faster access to more granular information and more rapid switching between patient charts, as these users are more likely to view more patients in a given session.

We also observe differences in HIE use measure correlations across Browsers and Regulars, which offers insight into use attribute trade-offs across Browsers and Regulars that can further assist with system design. For example, we may assume that extended session duration is uniformly paired with greater volume of use. While this assumption is supported among Regulars in terms of viewing more patient records during longer sessions, it is not clear that this assumption holds for Browsers, who don't demonstrate a strong correlation between session duration and any other use attribute in particular. Understanding these relationships can help system designers anticipate what functions are more and less important to different user experiences. The example further motivates the prominence of patient search functionalities during Regulars' sessions to facilitate easier movement between charts, for instance.

<u>Contributions and Implications for Future Work</u>

To our knowledge, this is the first study to apply cluster analysis to HIE use log data at the user level to better understand groups of user-level patterns of HIE use. While other studies have used similar methods to classify use sessions according to use patterns [4.7,4.24], less work has been done to understand user group variation or to analyze how use of health IT tools varies across user groups [4.24,4.33–4.35]. In doing so, our work adds to the levels of analysis present in the HIE use literature, which frequently occurs at the individual session, organization, and exchange network levels [4.31]. While these are important levels of analysis to understand outcomes like adoption, network breadth, and architectural integration, they do not provide insight into the experience of the ultimate end-users of these systems. To this end, our study contributes to the understanding of user-level differences in HIE use that cross organizations and clinical roles. We find substantial variation across our five user clusters, which, while not tied to clinical decision-making or patient care outcomes, offers insight into how systems can incorporate user profiles and be responsive in configuration to different types of users, a common practice in modern software development but a rare occurrence in one-size-fits all HIE systems [4.7,4.36]. One way in which HIE systems could utilize these findings is to provide faster access to information categories that certain user types frequently access. For example, we find that Superusers access content pertaining to patient vital signs second-most frequently after viewing summary information, which differs from Regulars who more frequently access laboratory content. An HIE system could respond to this by making these content areas more readily accessible for each user group (e.g. with a prominent link on the summary page) or include these data on group members' landing pages. This customization is more technically feasible and appropriate at the user level than at the session level, as it is difficult for an HIE system to anticipate the type of session a user will be engaging in, whereas user type is directly observable and can be informed based on historical use measures, as we have done in our cluster analysis presented above. Future work should examine the impact that these system design changes have on user experience and acceptance, to better understand the precise system designs that will facilitate the broadest use and have downstream implications for clinical decision-making and care quality.

In applying the Politi, et al. framework of multidimensional HIE use, this work aims to contribute to the systemization of HIE use literature, a key challenge as settings, architectural types, workflows, clinical data availability, and other factors vary widely across HIE system implementations and efforts [4.65,4.66]. These variations make large scale, nationally representative HIE use log data difficult - if not impossible - to acquire, which in turn renders studies of HIE use inherently limited in their generalizability to the settings and environments in which they occur. Given these constraints, consistent application of measurement frameworks is one of the few tools researchers have at their disposal to improve the external validity of findings regarding the usage and effects of HIE [4.31]. Multiple studies employing high-fidelity, theoretically informed measures of use are needed to better understand the effects of HIE use on care quality [4.67,4.68]. The careful and consistent application of frameworks such as this one, the Massetti and Zmud framework of electronic data interchange [4.69], and the Burton-Jones and Straub framework of information system usage measure richness [4.70] is critical to building the body of evidence on the impact of HIE use on care quality and to rigorously identifying the specific nature of HIE use and mechanisms that underlie any observed effects.

Furthermore, the current work contributes to the development of these measurement frameworks by extending the current framework to include two additional attributes of HIE system use: efficiency and participation. In particular, the attribute of efficiency is important for health IT system use in general and HIE system use specifically, as information retrieval tasks are often undertaken in time-constrained environments like EDs. Efficient access to and navigation within HIE systems is important for, first, user acceptance, and second, conditional on that acceptance and use, any impact of HIE on care quality [4.8]. Our findings demonstrate that user groups do in fact differ substantially in efficiency, which may be a latent factor in system under-use or rejection and thus has implications for both HIE system design and implementation. In particular, more tightly integrated systems such as those with integrated login for users and/or direct links or access to HIE records from within EHRs may offer more efficient user experiences [4.31]. Future work should explore the extent to which HIE systems designed with efficiency in mind have greater acceptance and use, as these designs may hold greater potential for improvements to care quality.

Conclusion

We studied users of an HIE system over three years and used system log data to compute measures of use volume, diversity, granularity, duration, content, efficiency, and participation. We applied cluster analysis at the user level, to identify five discrete groups of users as defined by their aggregate use patterns across sessions. User clusters were primarily differentiated by use volume, session duration, and efficiency measures. We further analyzed differences in use measures and their correlations across two groups of non-outlier users, which we called Browsers and Regulars. Our findings indicate variation in user-level patterns of HIE use, which may not be well-accommodated in one-size-fits-all HIE systems. Designers of voluntary use systems like HIE should consider variation in system use when designing user profiles and workflows in HIE systems, as well as emphasize ways to reduce inefficient use of the system.

References

4.1 Walker J, Pan E, Johnston D, et al. The value of health care information exchange and interoperability. Health Aff 2005;Suppl Web Exclusives:W5–10 – W5–18. doi:10.1377/hlthaff.w5.10

4.2 Vest JR, Gamm LD. Health information exchange: persistent challenges and new strategies. J Am Med Inform Assoc 2010;17:288–94. doi:10.1136/jamia.2010.003673

4.3 DeSalvo K, Savage M. The Nationwide Interoperability Roadmap And The ONC's And CMS's Proposed New Regulations: Are We Halfway There Yet? Health Affairs Blog. 2019.https://www.healthaffairs.org/do/10.1377/hblog20190621.419379/full/?utm_source=Newsletter&utm_medium=email&utm_content=Executive+Order+On+Health+Care+Price+Transparency%3B+The+Nationwide+Interoperability+Roadmap%3B+NPs+And+PAs+As+Primary+Care+Providers+For+Complex+Patients&utm_campaign=HAT+6-25-19 (accessed 18 Jul 2019).

4.4 Adler-Milstein J, Jha AK. HITECH Act Drove Large Gains In Hospital Electronic Health Record Adoption. Health Aff Published Online First: 5 September 2017.http://www.healthaffairs.org/doi/10.1377/hlthaff.2016.1651 (accessed 9 Nov 2017).

4.5 Washington V, DeSalvo K, Mostashari F, et al. The HITECH Era and the Path Forward. N Engl J Med 2017;377:904–6. doi:10.1056/NEJMp1703370

4.6 Verma S. Remarks by CMS Administrator Seema Verma at the HIMSS18 Conference. 2018.https://www.cms.gov/Newsroom/MediaReleaseDatabase/Press-releases/2018-Press-releases-items/2018-03-06-2.html (accessed 5 Jul 2018).

4.7 Politi L, Codish S, Sagy I, et al. Use patterns of health information exchange through a multidimensional lens: conceptual framework and empirical validation. J Biomed Inform 2014;52:212–21. doi:10.1016/j.jbi.2014.07.003

4.8 Frisse ME, Holmes RL. Estimated financial savings associated with health information exchange and ambulatory care referral. J Biomed Inform 2007;40:S27–32. doi:10.1016/j.jbi.2007.08.004

4.9 Office of the National Coordinator for Health IT. Office-Based Physician Health IT Adoption and Use. Health IT Dashboard | Data. 2019.https://dashboard.healthit.gov/datadashboard/documentation/physician-health-it-adoption-use-data-documentation.php (accessed 2 Oct 2019).

4.10 Furukawa MF, Patel V, Charles D, et al. Hospital Electronic Health Information Exchange Grew Substantially In 2008–12. Health Aff 2013;32:1346–54. doi:10.1377/hlthaff.2013.0010

4.11 Vest JR, Zhao H, Jasperson J, et al. Factors motivating and affecting health information exchange usage. J Am Med Inform Assoc 2011;18:143–9. doi:10.1136/jamia.2010.004812

4.12 Rudin RS, Motala A, Goldzweig CL, et al. Usage and effect of health information exchange: a systematic review. Ann Intern Med 2014;161:803–11. doi:10.7326/M14-0877

4.13 Vest JR, Unruh MA, Casalino LP, et al. The complementary nature of query-based and directed health information exchange in primary care practice. J Am Med Inform Assoc Published Online First: 8 October 2019. doi:10.1093/jamia/ocz134
4.14 Vest JR, Grinspan ZM, Kern LM, et al. Using a health information exchange system for imaging information: patterns and predictors. AMIA Annu Symp Proc 2013;2013:1402–11.https://www.ncbi.nlm.nih.gov/pubmed/24551416
4.15 Berwick DM, Nolan TW, Whittington J. The Triple Aim: Care, Health, And Cost. Health Aff 2008;27:759–69. doi:10.1377/hlthaff.27.3.759
4.16 Sheikh A, Sood HS, Bates DW. Leveraging health information technology to achieve the 'triple aim' of healthcare reform. J Am Med Inform Assoc 2015;22:849–56. doi:10.1093/jamia/ocv022
4.17 Vest JR, Jasperson 'jon Sean, Zhao H, et al. Use of a health information exchange system in the emergency care of children. BMC Med Inform Decis Mak 2011;11:78. doi:10.1186/1472-6947-11-78
4.18 Vest JR, Gamm LD, Ohsfeldt RL, et al. Factors associated with health information exchange system usage in a safety-net ambulatory care clinic setting. J Med Syst 2012;36:2455–61. doi:10.1007/s10916-011-9712-3
4.19 Johnson KB, Unertl KM, Chen Q, et al. Health information exchange usage in emergency departments and clinics: the who, what, and why. J Am Med Inform Assoc 2011;18:690–7. doi:10.1136/amiajnl-2011-000308
4.20 Li X, Xue Y, Malin B. Towards Understanding the Usage Pattern of Web-based Electronic Medical Record Systems. World Wirel Mob Multimed Netw 2011;2011. doi:10.1109/WoWMoM.2011.5986195
4.21 Nirel N, Rosen B, Sharon A, et al. The impact of an integrated hospital-community medical information system on quality and service utilization in hospital departments. Int J Med Inform 2010;79:649–57. doi:10.1016/j.ijmedinf.2010.06.005
4.22 Hripcsak G, Sengupta S, Wilcox A, et al. Emergency department access to a longitudinal medical record. J Am Med Inform Assoc 2007;14:235–8. doi:10.1197/jamia.M2206
4.23 Ben-Assuli O, Shabtai I, Leshno M, et al. EHR in emergency rooms: exploring the effect of key information components on main complaints. J Med Syst 2014;38:36. doi:10.1007/s10916-014-0036-y
4.24 Vest JR, Jasperson 'jon Sean. How are health professionals using health information exchange systems? Measuring usage for evaluation and system improvement. J Med Syst 2012;36:3195–204. doi:10.1007/s10916-011-9810-2
4.25 Park H, Lee S-I, Hwang H, et al. Can a health information exchange save healthcare costs? Evidence from a pilot program in South Korea. Int J Med Inform 2015;84:658–66. doi:10.1016/j.ijmedinf.2015.05.008
4.26 Cross DA, McCullough JS, Banaszak-Holl J, et al. Health information exchange between hospital and skilled nursing facilities not associated with lower readmissions. Health Serv Res Published Online First: 10 October 2019. doi:10.1111/1475-6773.13210
4.27 Chen ES, Cimino JJ. Automated discovery of patient-specific clinician information needs using clinical information system log files. AMIA Annu Symp Proc 2003;:145–9.https://www.ncbi.nlm.nih.gov/pubmed/14728151

4.28 Chen ES, Cimino JJ. Patterns of usage for a Web-based clinical information system. Stud Health Technol Inform 2004;107:18–22.https://www.ncbi.nlm.nih.gov/pubmed/15360766
4.29 Cross DA. Electronic Information Sharing to Improve Post-Acute Care Transitions. 2018.https://deepblue.lib.umich.edu/handle/2027.42/146031
4.30 Ben-Assuli O, Shabtai I, Leshno M. Using electronic health record systems to optimize admission decisions: the Creatinine case study. Health Informatics J 2015;21:73–88. doi:10.1177/1460458213503646
4.31 Vest JR, Jasperson J. What should we measure? Conceptualizing usage in health information exchange. J Am Med Inform Assoc 2010;17:302–7. doi:10.1136/jamia.2009.000471
4.32 Cresswell KM, Bates DW, Sheikh A. Ten key considerations for the successful implementation and adoption of large-scale health information technology. J Am Med Inform Assoc 2013;20:e9–13. doi:10.1136/amiajnl-2013-001684
4.33 Zheng K, Padman R, Johnson MP, et al. An adoption study of a clinical reminder system in ambulatory care using a developmental trajectory approach. Stud Health Technol Inform 2004;107:1115–9.https://www.ncbi.nlm.nih.gov/pubmed/15360986
4.34 Zheng K, Padman R, Johnson MP, et al. Understanding technology adoption in clinical care: clinician adoption behavior of a point-of-care reminder system. Int J Med Inform 2005;74:535–43. doi:10.1016/j.ijmedinf.2005.03.007
4.35 Johnson MP, Zheng K, Padman R. Modeling the longitudinality of user acceptance of technology with an evidence-adaptive clinical decision support system. Decis Support Syst 2014;57:444–53. doi:10.1016/j.dss.2012.10.049
4.36 Unertl KM, Johnson KB, Lorenzi NM. Health information exchange technology on the front lines of healthcare: workflow factors and patterns of use. J Am Med Inform Assoc 2012;19:392–400. doi:10.1136/amiajnl-2011-000432
4.37 Gagnon M-P, Desmartis M, Labrecque M, et al. Systematic review of factors influencing the adoption of information and communication technologies by healthcare professionals. J Med Syst 2012;36:241–77. doi:10.1007/s10916-010-9473-4
4.38 Rochester Regional Health Information Organization. About Us. Rochester RHIO. https://rochesterrhio.org/AboutUs (accessed 22 Nov 2019).
4.39 Vest JR, Unruh MA, Shapiro JS, et al. The associations between query-based and directed health information exchange with potentially avoidable use of health care services. Health Serv Res Published Online First: 21 May 2019. doi:10.1111/1475-6773.13169
4.40 Rochester Regional Health Information Organization. Data Sources. Rochester RHIO. https://rochesterrhio.org/DataSources (accessed 22 Nov 2019).
4.41 Shabo A. Clinical Document Architecture. Encyclopedia of Database Systems. 2016;:1–2. doi:10.1007/978-1-4899-7993-3_59-2
4.42 Vest JR, Kern LM, Silver MD, et al. The potential for community-based health information exchange systems to reduce hospital readmissions. J Am Med Inform Assoc 2015;22:435–42. doi:10.1136/amiajnl-2014-002760

4.43 Campion TR Jr, Edwards AM, Johnson SB, et al. Health information exchange system usage patterns in three communities: practice sites, users, patients, and data. Int J Med Inform 2013;82:810–20. doi:10.1016/j.ijmedinf.2013.05.001
4.44 HRSA. Federally Qualified Health Centers. Official web site of the U.S. Health Resources & Services Administration. https://www.hrsa.gov/opa/eligibility-and-registration/health-centers/fqhc/index.html (accessed 22 Nov 2019).
4.45 Parker C, Weiner M, Reeves M. Health information exchanges--Unfulfilled promise as a data source for clinical research. Int J Med Inform 2016;87:1–9. doi:10.1016/j.ijmedinf.2015.12.005
4.46 Lin SC, Hollingsworth JM, Adler-Milstein J. Alternative payment models and hospital engagement in health information exchange. Am J Manag Care 2019;25:e1–6.https://www.ncbi.nlm.nih.gov/pubmed/30667611
4.47 Moe WW. Buying, Searching, or Browsing: Differentiating Between Online Shoppers Using In-Store Navigational Clickstream. J Consum Psychol 2003;13:29–39. doi:10.1207/S15327663JCP13-1&2_03
4.48 Eason K, Richardson S, Yu L. Patterns of use of electronic journals. Journal of Documentation 2000;56:477–504. doi:10.1108/EUM0000000007124
4.49 Van den Poel D, Buckinx W. Predicting online-purchasing behaviour. Eur J Oper Res 2005;166:557–75. doi:10.1016/j.ejor.2004.04.022
4.50 Kannampallil TG, Denton CA, Shapiro JS, et al. Efficiency of Emergency Physicians: Insights from an Observational Study using EHR Log Files. Appl Clin Inform 2018;9:99–104. doi:10.1055/s-0037-1621705
4.51 Venkatesh V, Morris MG, Davis GB, et al. User Acceptance of Information Technology: Toward a Unified View. Miss Q 2003;27:425–78. doi:10.2307/30036540
4.52 Kaufman L, Rousseeuw PJ. Clustering large applications (Program CLARA). Finding groups in data: an introduction to cluster analysis 2008;:126–63.
4.53 Tankersley J. No Virus Deaths by Mid-May? White House Economists Say They Didn’t Forecast Early End to Fatalities. The New York Times. 2020.https://www.nytimes.com/2020/05/06/business/coronavirus-white-house-economists.html (accessed 6 May 2020).
4.54 James G, Witten D, Hastie T, et al. An Introduction to Statistical Learning: with Applications in R. Springer, New York, NY 2013. doi:10.1007/978-1-4614-7138-7
4.55 Diedenhofen B, Musch J. cocor: a comprehensive solution for the statistical comparison of correlations. PLoS One 2015;10:e0121945. doi:10.1371/journal.pone.0121945
4.56 RStudio Team. R Studio. 2015. http://www.rstudio.com/
4.57 R Core Team. R: A Language and Environment for Statistical Computing. Vienna, Austria: : R Foundation for Statistical Computing 2018. https://www.R-project.org/
4.58 Wickham H. The tidyverse. R package ver 1 1 1 Published Online First: 2017.https://slides.nyhackr.org/presentations/The-Tidyverse_Hadley-Wickham.pdf
4.59 Dowle M, Srinivasan A. data.table: Extension of `data.frame`. 2019. https://CRAN.R-project.org/package=data.table
4.60 Maechler M, Rousseeuw P, Struyf A, et al. cluster: Cluster Analysis Basics and Extensions. 2019. https://www.rdocumentation.org/packages/cluster/versions/2.1.0

4.61 Kassambara A. rstatix: Pipe-Friendly Framework for Basic Statistical Tests. 2019. https://cran.r-project.org/web/packages/rstatix/index.html
4.62 O'Brien RG, Kaiser MK. MANOVA method for analyzing repeated measures designs: an extensive primer. Psychol Bull 1985;97:316–33.https://www.ncbi.nlm.nih.gov/pubmed/3983301
4.63 Genes N, Shapiro J, Vaidya S, et al. Adoption of health information exchange by emergency physicians at three urban academic medical centers. Appl Clin Inform 2011;2:263–9. doi:10.4338/ACI-2011-02-CR-0010
4.64 Thorn SA, Carter MA, Bailey JE. Emergency physicians' perspectives on their use of health information exchange. Ann Emerg Med 2014;63:329–37. doi:10.1016/j.annemergmed.2013.09.024
4.65 McCarthy DB, Propp K, Cohen A, et al. Learning from health information exchange technical architecture and implementation in seven beacon communities. EGEMS (Wash DC) 2014;2:1060. doi:10.13063/2327-9214.1060
4.66 Adler-Milstein J, Jha AK. Health information exchange among U.S. hospitals: who's in, who's out, and why? Healthc (Amst) 2014;2:26–32. doi:10.1016/j.hjdsi.2013.12.005
4.67 Rahurkar S, Vest JR, Menachemi N. Despite The Spread Of Health Information Exchange, There Is Little Evidence Of Its Impact On Cost, Use, And Quality Of Care. Health Aff Published Online First: March 2015.https://www.healthaffairs.org/doi/abs/10.1377/hlthaff.2014.0729 (accessed 25 Feb 2018).
4.68 Menachemi N, Rahurkar S, Harle CA, et al. The benefits of health information exchange: an updated systematic review. J Am Med Inform Assoc Published Online First: 28 April 2018. doi:10.1093/jamia/ocy035
4.69 Massetti B, Zmud RW. Measuring the Extent of EDI Usage in Complex Organizations: Strategies and Illustrative Examples. Miss Q 1996;20:331–45. doi:10.2307/249659
4.70 Burton-Jones A, Straub DW. Reconceptualizing System Usage: An Approach and Empirical Test. Information Systems Research 2006;17:228–46. doi:10.1287/isre.1060.0096

Chapter 5: Conclusion

Summary of Findings

This dissertation has examined several dimensions of HIE use in the context of primary care, an under-represented area of HIE research [5.1,5.2] and an important hub for care coordination efforts [5.3]. Furthermore, numerous efforts to reform health care delivery in the US are rooted in primary care [5.4–5.6], and depend upon the adoption and use of interoperable health IT to realize the goals of improved quality and lower costs [5.4,5.7,5.8]. Thus, this work is situated at the intersection of primary care and health IT use, and focuses on the use of HIE. This dissertation therefore also sits at the juncture of health services research, health informatics, and health policy, and contributes to each of these domains.

Chapter 2 analyzed overall rates of HIE use and practice and market factors associated with HIE, offering insight into the conditions and policies that foster more or less provider HIE. We found somewhat low rates of overall HIE use among primary care providers (43% of referrals were sent with eSCR), indicating that even among providers with the capability to exchange data, a usage gap remains. The EHR vendor the practice utilized demonstrated a relationship with HIE use, suggesting that HIE may be more readily facilitated by certain vendors. More work is needed to better understand the mechanisms underlying these vendor-based differences, which may in turn inform regulatory efforts to reduce forms of "information blocking" by EHR vendors. We also find that HIE use is greater among primary care providers in counties that do not suffer from health care provider shortages. This could be driven by availability of technologically equipped exchange partners, availability of specialists, established referral networks, or some other set of factors. Future federal efforts may seek to focus energy on closing this HIE use gap, as primary care providers in less well-resourced areas are likely to encounter more chronically ill patients requiring effective care coordination and therefore need robust HIE to facilitate that coordination.

Chapter 3 examined the prevalence of team-based use of HIE in the context of primary care delivery reform, finding that over 85% of visits with any use of the HIE did so in a manner congruent with team-based models of care. While overall usage rates of the HIE remained quite low, consistent with previous research on similar voluntary use systems [5.9], those visits involving HIE did so overwhelmingly in a team-based manner. This study offers quantitative support for qualitative studies emphasizing the importance of HIE in team-based care [5.5,5.10,5.11]. It also provides encouraging evidence that existing HIE systems can support primary care delivery reform; this in turn offers support for additional development of these policies and programs. Observed HIE system use supports the notion that these systems can support team-based models of care. Furthermore, we found that team-based use is at best not associated with reduced breadth of information viewed in the HIE, but we did not find support for our hypothesis that team-based use would be associated with more information categories viewed by the team relative to non-team-based use. This finding does not support the hypothesis that delegated and distributed use of HIE systems will facilitate broader information retrieval and more comprehensive knowledge about the patient, however we do find that larger teams engage in broader HIE use. Future research in this area should explore the underlying information needs of teams in primary care, and to the extent that they differ from individual provider needs, seek to measure that dimension of information seeking in future analyses. We also found that the depth of use among teams tended to be lower both before and after a patient visit, implying that teams spent relatively more time viewing summative information (vs. individual result data) than individual providers. This supports previous work noting that providers tend to use HIE systems to look at more detailed and specific information [5.12,5.13]. One of the key values of HIE systems is that they can provide summative views of information, whereas traditional methods of exchange such as fax do not collate information for quick review. The tendency of teams, when using HIE, to give more attention to summative pages provides support for this fundamental component of HIE system value in collating and allowing for rapid review of large quantities of clinical information that otherwise would require time-consuming perusal of entire patient charts. Future work can extend this knowledge by linking these measures of team-based HIE use to care quality and cost outcomes, to quantify the extent to which technology use in particular contributes to the goals of delivery reform.

Finally, in chapter 4 we examined user-level patterns of HIE use, identifying five discrete types of users that cross-cut user roles and uncovering two distinct tiers of non-outlier users that are often homogenized and only distinguished from outlier users (e.g. non-users or superusers). User-level analyses of HIE system use have been rare [5.12, 5.14], and this study explores important variation in user patterns that can inform the construction of user profiles and dynamic system interfaces based on past HIE use that anticipate and meet users' distinct information needs. For example, more "regular" users who are not superusers appear to use longer duration sessions to view a greater volume of patient charts, rather than view more granular information about a single patient. This relationship is not as clear among less regular users ("Browsers"). This finding suggests that for Regular users, functionality to switch between patient charts may be relatively more important than making high-granularity information readily accessible. Furthermore, users demonstrated variation in use efficiency, with higher-frequency users demonstrating returns to their efficiency of HIE use. This supports the notion that ease of access to information within the HIE is critical to widespread HIE use, as administrative burdens such as logins and failed patient searches contribute to low provider uptake [5.15,5.16]. Specifically, the use of single-sign-on web services and integration of HIE access within EHRs may improve HIE use efficiency, ease the burden of access to HIE, drive greater use, and more effectively improve care quality. Beyond its empirical findings, chapter 4 also extends a six-attribute framework of multidimensional HIE use [5.17], by adding a session-level attribute of use efficiency and a user-level attribute of participation in HIE system use. Our findings underscore the importance of measuring use efficiency and provide researchers with a framework and suggested measures to develop replicable evidence regarding the efficacy of specific types of HIE use. Variation in HIE use measurement has been a core challenge to developing generalizable findings regarding the impact of HIE on care quality and cost [5.2,5.18], and absent national HIE use log data, measurement frameworks are a critically important tool for improving this literature [5.14].

Contributions to Health Information Exchange Literature

These findings represent several contributions to the HIE literature, in both the "barriers and facilitators" and "HIE use" streams (Figure 1.1). Chapter 2 refines our understanding of the barriers and facilitators to HIE use as the first study to quantify the volume of HIE use at the provider level in a nation-wide sample of providers, rather than at the organizational level. Furthermore, we identify key factors that may influence the rate of HIE use among providers, in particular EHR vendor, beneficiary mix, and location within a health professional shortage area. Chapter 3 contributes to the HIE use literature as the first study to utilize an explicit measure of team-based HIE use, rooted in regulatory proposals for improving quality measurement, and quantifies the degree to which HIE is being used in a manner congruent with team-based care delivery models. We find that this is indeed occurring; previous research articulated levels of technology adoption and the effects on cost, quality, and patient outcomes [5.8,5.19], but did not measure the nature of the use of these technologies. We provide new evidence that helps to contextualize the technology use mechanisms that may play a role in these outcomes. We also offer new evidence regarding the differences (or lack thereof) between team-based HIE use and non-team-based HIE use, a further refinement of the literature covering differences in the nature of HIE use by distinct types of users. Chapter 4 contributes to the "HIE use" literature sub-stream via a novel user-level analysis of HIE use, deploying and extending a conceptual framework to include replicable measures of use efficiency and participation. We identify five discrete groups of HIE system users that cross-cut clinical roles. Previous research has focused on classifying session-level measures of use [5.12,5.17,5.20]; our work addresses calls for user-level analyses [5.14] and identifies two tiers of "typical" HIE users largely differentiated by participation, use volume, and efficiency measures. These user types can be utilized in dynamic approaches to HIE workflow design and provide insight into the trade-offs that users demonstrate in what they prioritize in health IT system use. Moreover, this dissertation contributes to the knowledge base regarding HIE in the context of primary care, which, like many other care settings, has been under-represented in the HIE literature despite its critical importance to care coordination.

Directions for Future Research

This body of work has implications for health services researchers and health informatics researchers as well as policy researchers, especially those focused on health IT and primary care delivery reform efforts. First, health services researchers studying primary care delivery reform can focus future work on understanding appropriate levels of HIE use and the relationship between the volume and nature of HIE use and primary care quality outcomes like chronic disease management. As noted previously, while normative levels of HIE use remain elusive, study of "missed opportunities" for exchange will be critical to quantifying this gap and tracking its closure. Furthermore, the body of evidence regarding HIE's impact on clinical quality outcomes in particular remains sparse [5.2,5.21,5.22]. Finally, detailed measures of different HIE use attributes allow health services researchers to analyze the relative contributions or effects that different types of HIE and health IT use have on those outcomes. For example, researchers may be interested in the particular attributes of HIE use that underlie ED admission decisions or that have an outsized impact on reducing readmission rates. Additionally, studies could examine the relationship between specific types of HIE use for care coordination on clinical outcomes such as controlled hypertension or diabetes. Understanding these details is important for quantifying the value of health IT and HIE, and can inform system implementation, training, workflow redesign, and regulatory programs aiming to incentivize the types of HIE use that contribute directly to quality goals. Second, health services and policy researchers can utilize the HIE use measures applied in chapters three and four as process measures in studies of care quality, linking organizational and system structures to outcomes of interest via observed patterns of use representing the care process [5.23]. Third, health informatics researchers studying the impacts of system-level differences like interface designs and integration capabilities can utilize measures like efficiency, volume, and granularity as outcomes to analyze the impact system changes like single-sign-on and EHR integration on the nature of HIE system use. This also has implications for health IT policy researchers who may be interested in identifying the most efficacious of these system-level approaches to inform regulatory measures and incentive programs that aim to move health IT use towards the most evidence-based design and implementation approaches. Fourth, informatics researchers utilizing log data from EHRs and HIE systems can apply the Politi, et al. framework as well as the extensions articulated herein to improve standardization in approaches to HIE use measurement and external validity of findings. We encourage informatics researchers to replicate findings from chapter 3 in different HIE systems, care settings, and geographies, to reveal variation in user groups and use patterns across these dimensions that can further inform system design and implementation practices. Furthermore, we echo Politi, et al. in our encouragement to further extend this framework, ideally adapting it to measure multidimensional use of health IT tools outside the context of HIE. Fifth, these same researchers can deepen our understanding of EHR vendor-based differences in HIE use illuminated in chapter 2. For example, EHR log data may capture the patients for whom eSCRs were sent, and compare these patients' outcomes to similar patients for whom a referral was sent without eSCR. Rates of use can then be compared across EHR vendors, controlling for patient, visit, and organizational characteristics. However, for this work to be feasible, considerable progress must be made in standardizing EHR use measurements to allow for cross-platform, multi-institution studies [5.24]. Furthermore, these attributes and measures of use are additional candidates for the evaluation of specific types of health IT system use and quality outcomes noted previously.

Despite progress in adoption and massive federal investment, widespread interoperable HIE remains aspirational for the US health care system. While technological capabilities have advanced considerably, major gaps remain in the network of health IT systems supporting care delivery. Providers and policymakers are keen on realizing the returns to this investment in the form of higher quality and better coordinated care; this return depends in large part on interoperability and use of high-fidelity HIE [5.25,5.26]. This is particularly important in primary care settings, which are at the center of the US health care system and often serve as care coordinators and hubs of patient information. This dissertation has examined provider use of HIE across a number of dimensions, and offers novel evidence and methodological development that improves our understanding of the role of HIE use in the US health care system's progress towards improved quality.

References

5.1 Dobrow MJ, Bytautas JP, Tharmalingam S, et al. Interoperable Electronic Health Records and Health Information Exchanges: Systematic Review. JMIR Med Inform 2019;7:e12607. doi:10.2196/12607

5.2 Menachemi N, Rahurkar S, Harle CA, et al. The benefits of health information exchange: an updated systematic review. J Am Med Inform Assoc Published Online First: 28 April 2018. doi:10.1093/jamia/ocy035

5.3 O'Malley AS, Tynan A, Cohen GR, et al. Coordination of care by primary care practices: strategies, lessons and implications. Res Brief 2009;:1–16.https://www.ncbi.nlm.nih.gov/pubmed/19452679

5.4 David G, Saynisch PA, Smith-McLallen A. The economics of patient-centered care. J Health Econ 2018;59:60–77. doi:10.1016/j.jhealeco.2018.02.012

5.5 Vest JR, Kern LM, Jung H-Y, et al. Patient-centered medical homes: observable types derived from national recognition assessment scores. J Ambul Care Manage 2015;38:144–52. doi:10.1097/JAC.0000000000000064

5.6 Kern LM, Edwards A, Kaushal R. The Patient-Centered Medical Home and Associations With Health Care Quality and Utilization: A 5-Year Cohort Study. Ann Intern Med 2016;164:395–405. doi:10.7326/M14-2633

5.7 Adler-Milstein J, Cohen GR. Implementing the IT infrastructure for health reform: adoption of health IT among patient-centered medical home practices. AMIA Annu Symp Proc 2013;2013:11–6.https://www.ncbi.nlm.nih.gov/pubmed/24551318

5.8 Adler-Milstein J, Cohen GR, Markovitz A, et al. The Impact of HIT on Cost and Quality in Patient-Centered Medical Home Practices. AMIA Annu Symp Proc 2014;2014:232–9.https://www.ncbi.nlm.nih.gov/pubmed/25954324

5.9 Vest JR, Unruh MA, Casalino LP, et al. The complementary nature of query-based and directed health information exchange in primary care practice. J Am Med Inform Assoc Published Online First: 8 October 2019. doi:10.1093/jamia/ocz134

5.10 Morton S, Shih SC, Winther CH, et al. Health IT-Enabled Care Coordination: A National Survey of Patient-Centered Medical Home Clinicians. Ann Fam Med 2015;13:250–6. doi:10.1370/afm.1797

5.11 Richardson JE, Vest JR, Green CM, et al. A needs assessment of health information technology for improving care coordination in three leading patient-centered medical homes. J Am Med Inform Assoc 2015;22:815–20. doi:10.1093/jamia/ocu039

5.12 Vest JR, Jasperson 'jon Sean. How are health professionals using health information exchange systems? Measuring usage for evaluation and system improvement. J Med Syst 2012;36:3195–204. doi:10.1007/s10916-011-9810-2

5.13 Vest JR, Grinspan ZM, Kern LM, et al. Using a health information exchange system for imaging information: patterns and predictors. AMIA Annu Symp Proc 2013;2013:1402–11.https://www.ncbi.nlm.nih.gov/pubmed/24551416

5.14 Vest JR, Jasperson J. What should we measure? Conceptualizing usage in health information exchange. J Am Med Inform Assoc 2010;17:302–7. doi:10.1136/jamia.2009.000471

5.15 Thorn SA, Carter MA, Bailey JE. Emergency physicians' perspectives on their use of health information exchange. Ann Emerg Med 2014;63:329–37. doi:10.1016/j.annemergmed.2013.09.024
5.16 Genes N, Shapiro J, Vaidya S, et al. Adoption of health information exchange by emergency physicians at three urban academic medical centers. Appl Clin Inform 2011;2:263–9. doi:10.4338/ACI-2011-02-CR-0010
5.17 Politi L, Codish S, Sagy I, et al. Use patterns of health information exchange through a multidimensional lens: conceptual framework and empirical validation. J Biomed Inform 2014;52:212–21. doi:10.1016/j.jbi.2014.07.003
5.18 Rudin RS, Motala A, Goldzweig CL, et al. Usage and effect of health information exchange: a systematic review. Ann Intern Med 2014;161:803–11. doi:10.7326/M14-0877
5.19 David G, Gunnarsson C, Saynisch PA, et al. Do patient-centered medical homes reduce emergency department visits? Health Serv Res 2015;50:418–39. doi:10.1111/1475-6773.12218
5.20 Cross DA, McCullough JS, Banaszak-Holl J, et al. Health information exchange between hospital and skilled nursing facilities not associated with lower readmissions. Health Serv Res Published Online First: 10 October 2019. doi:10.1111/1475-6773.13210
5.21 Hersh WR, Totten AM, Eden K, et al. Chapter 14 - The Evidence Base for Health Information Exchange. In: Dixon BE, ed. Health Information Exchange. Academic Press 2016. 213–29. doi:10.1016/B978-0-12-803135-3.00014-1
5.22 Hincapie A, Warholak T. The Impact of Health Information Exchange on Health Outcomes. Appl Clin Inform 2011;02:499–507. doi:10.4338/ACI-2011-05-R-0027
5.23 Donabedian A. Evaluating the quality of medical care. Milbank Mem Fund Q 1966;44:Suppl:166–206.https://www.ncbi.nlm.nih.gov/pubmed/5338568
5.24 Sinsky CA, Rule A, Cohen G, et al. Metrics for assessing physician activity using electronic health record log data. J Am Med Inform Assoc Published Online First: 6 February 2020. doi:10.1093/jamia/ocz223
5.25 Walker J, Pan E, Johnston D, et al. The value of health care information exchange and interoperability. Health Aff 2005;Suppl Web Exclusives:W5–10 – W5–18. doi:10.1377/hlthaff.w5.10
5.26 Vest JR, Gamm LD. Health information exchange: persistent challenges and new strategies. J Am Med Inform Assoc 2010;17:288–94. doi:10.1136/jamia.2010.003673

Appendix A: Chapter 2 Supplemental Materials

Regression Model Details

$$\text{HIEVolume} = \alpha + \beta_1\text{PracticeSize} + \beta_2\text{EHRVendor} + \beta_3\text{HealthSystemMembership} + \beta_4\text{ProviderMarketShare} + \beta_5\text{AvgBeneficiaryAge} + \beta_6\text{AvgBeneficiaryHCCRiskScore} + \beta_7\text{PctBeneficiariesCKD} + \beta_8\text{PctBeneficiariesDiabetes} + \beta_9\text{PctBeneficiariesHypertension} + \beta_{10}\text{HSAConcentrationIndex} + \beta_{11}\text{NumberofProviderswEHRsinHSA} + \beta_{12}\text{HealthProfessionalShortageArea} + \beta_{13}\text{CountyMedianHouseholdIncome} + \beta_{14}\text{CountyPctPersonsinPoverty} + \beta_{15}\text{CountyMetroNonMetro} + \beta_{16}\text{StateHIEConsentPolicy} + \beta_{17}\text{ProviderGender} + \beta_{18}\text{ProviderYearsinPractice} + \varepsilon$$

Notes: Terms in red denote practice factors, green terms denote market factors, and blue terms denote control variables.

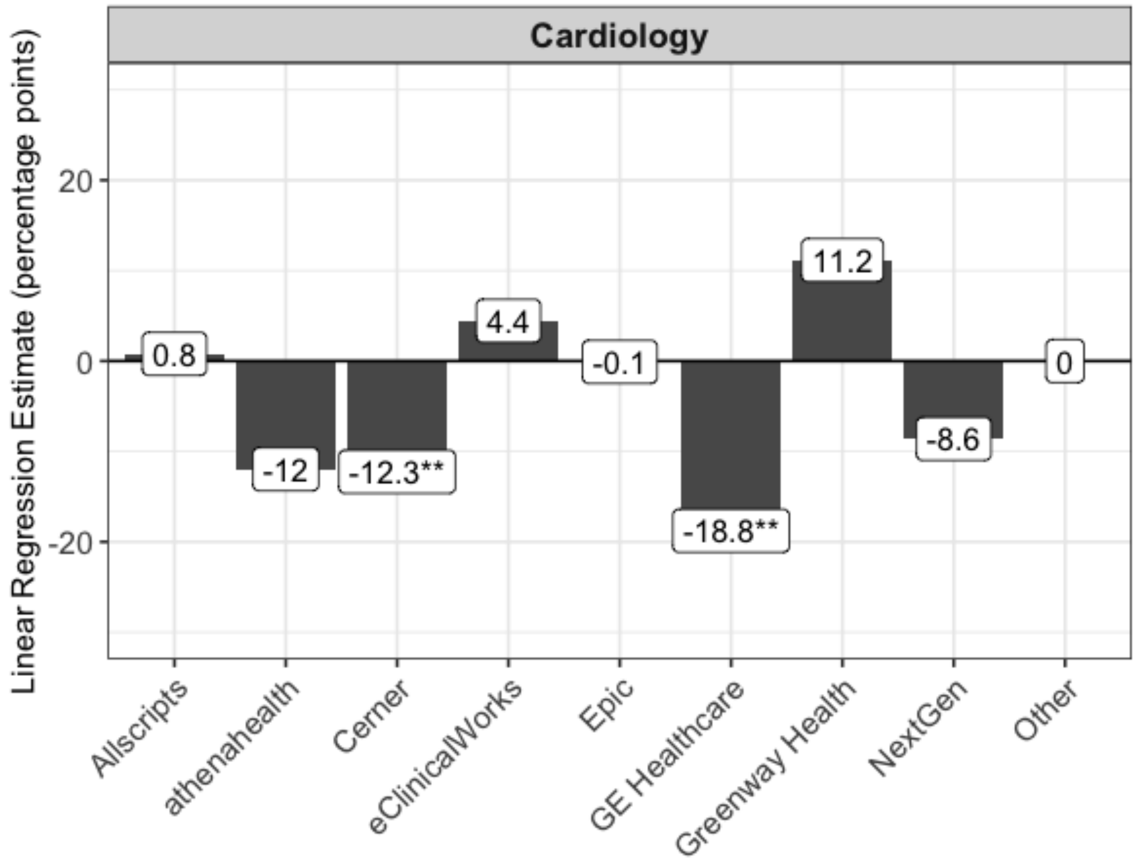
Table A1 Descriptive Statistics of Sample, Stratified by Provider Specialty

		Overall	Primary Care	Cardiology	Orthopedic Surgery	p
n		26095	22407	2193	1495	
% Referrals Sent w/ eSCR***		45.12 (28.12)	42.72 (27.05)	63.54 (30.86)	54.06 (27.81)	<0.001
Practice Factors						
Practice Size***	2 to 5	2729 (10.6)	2431 (11.1)	156 (7.2)	142 (9.5)	<0.001
	>51 providers	13765 (53.7)	12320 (56.0)	870 (40.0)	575 (38.6)	
	11 to 50	5864 (22.9)	4418 (20.1)	842 (38.7)	604 (40.6)	
	6 to 10	1809 (7.1)	1498 (6.8)	206 (9.5)	105 (7.1)	
	Solo practice	1484 (5.8)	1320 (6.0)	101 (4.6)	63 (4.2)	
EHR Vendor***	other	5966 (22.9)	4764 (21.3)	895 (40.8)	307 (20.5)	<0.001
	Allscripts	3132 (12.0)	2890 (12.9)	91 (4.1)	151 (10.1)	
	athenahealth, Inc.	2696 (10.3)	2216 (9.9)	21 (1.0)	459 (30.7)	
	Cerner Corporation	1040 (4.0)	835 (3.7)	179 (8.2)	26 (1.7)	
	eClinicalWorks, LLC	4661 (17.9)	4051 (18.1)	465 (21.2)	145 (9.7)	
	Epic Systems Corporation	3488 (13.4)	3381 (15.1)	33 (1.5)	74 (4.9)	
	GE Healthcare	1222 (4.7)	1127 (5.0)	45 (2.1)	50 (3.3)	
	Greenway Health, LLC	1075 (4.1)	797 (3.6)	200 (9.1)	78 (5.2)	
	NextGen Healthcare	2815 (10.8)	2346 (10.5)	264 (12.0)	205 (13.7)	
Health System Membership***	Not in a health system	17620 (67.5)	14845 (66.3)	1539 (70.2)	1236 (82.7)	<0.001
	In a health system	8475 (32.5)	7562 (33.7)	654 (29.8)	259 (17.3)	
Provider Market Share (w/in specialty)***		2.85 (8.11)	1.73 (4.84)	8.68 (15.02)	11.06 (18.18)	<0.001
Average Beneficiary Age***		72.65 (3.02)	72.46 (3.06)	75.00 (1.91)	72.05 (2.12)	<0.001
Average Beneficiary HCC Risk Score***		1.27 (0.38)	1.22 (0.36)	1.78 (0.30)	1.20 (0.21)	<0.001
% of Beneficiaries w/ CKD***		28.67 (10.80)	27.48 (10.33)	42.63 (7.50)	25.78 (6.17)	<0.001
% of Beneficiaries w/ Diabetes***		31.43 (8.92)	30.69 (8.81)	39.89 (6.79)	29.95 (6.52)	<0.001
% of Beneficiaries w/ Hypertension***		66.88 (8.84)	65.97 (8.96)	74.85 (1.12)	68.82 (7.08)	<0.001
Market Factors						
HSA Concentration Index***	Unconcentrated	24738 (94.8)	21763 (97.1)	1836 (83.7)	1139 (76.2)	<0.001
	Moderately Concentrated	516 (2.0)	171 (0.8)	163 (7.4)	182 (12.2)	

	Highly Concentrated	840 (3.2)	473 (2.1)	194 (8.8)	173 (11.6)	
Number of Providers with EHRs in HSA*		335.91 (456.79)	335.82 (457.55)	320.78 (426.97)	359.46 (486.07)	0.041
Number of Medicare Hospitals, county***		6.57 (10.66)	6.69 (10.93)	6.51 (9.46)	4.89 (7.65)	<0.001
Health Professional Shortage Area*	No Shortage	2973 (11.4)	2527 (11.3)	296 (13.5)	150 (10.0)	0.012
	Partial Shortage	460 (1.8)	398 (1.8)	38 (1.7)	24 (1.6)	
	Full Shortage	22613 (86.8)	19436 (86.9)	1857 (84.8)	1320 (88.4)	
Median Household Income, county***		60918.90 (16440.33)	61115.07 (16140.09)	60777.89 (19745.35)	58190.67 (15291.53)	<0.001
Percent of Persons in Poverty, county***		13.35 (4.70)	13.29 (4.69)	13.61 (4.82)	13.86 (4.68)	<0.001
Metro vs. Non-Metro (%)	Metro	23070 (88.6)	19845 (88.7)	1922 (87.7)	1303 (87.2)	0.084
	non-Metro	2976 (11.4)	2516 (11.3)	269 (12.3)	191 (12.8)	
State HIE Consent Policy***	NoPolicy	7398 (28.4)	6391 (28.5)	503 (22.9)	504 (33.7)	<0.001
	OptIn	5782 (22.2)	4680 (20.9)	805 (36.7)	297 (19.9)	
	OptOut	6508 (24.9)	5749 (25.7)	396 (18.1)	363 (24.3)	
	Other	6407 (24.6)	5587 (24.9)	489 (22.3)	331 (22.1)	
Controls						
Provider Gender(%)***	F	8348 (32.0)	8094 (36.1)	198 (9.0)	56 (3.7)	<0.001
	M	17747 (68.0)	14313 (63.9)	1995 (91.0)	1439 (96.3)	
Years in Practice***		23.79 (10.27)	23.51 (10.27)	26.57 (10.12)	23.85 (9.87)	<0.001

Notes: Values reported are averages, with standard deviation in parenthesis, unless otherwise noted. Statistical tests of significance are the rest of bivariate chi-squared analyses. Significance levels: *p<0.05 **p<0.01 ***p<0.001.

Figure A1 Relationship between EHR vendor and HIE use volume, cardiology



Other EHR vendors are the reference group, and constitute all vendors not in the top 8 most common
*p<0.05 **p<0.01 ***p<0.001

Figure A2 Relationship between EHR vendor and HIE volume, orthopedic surgery

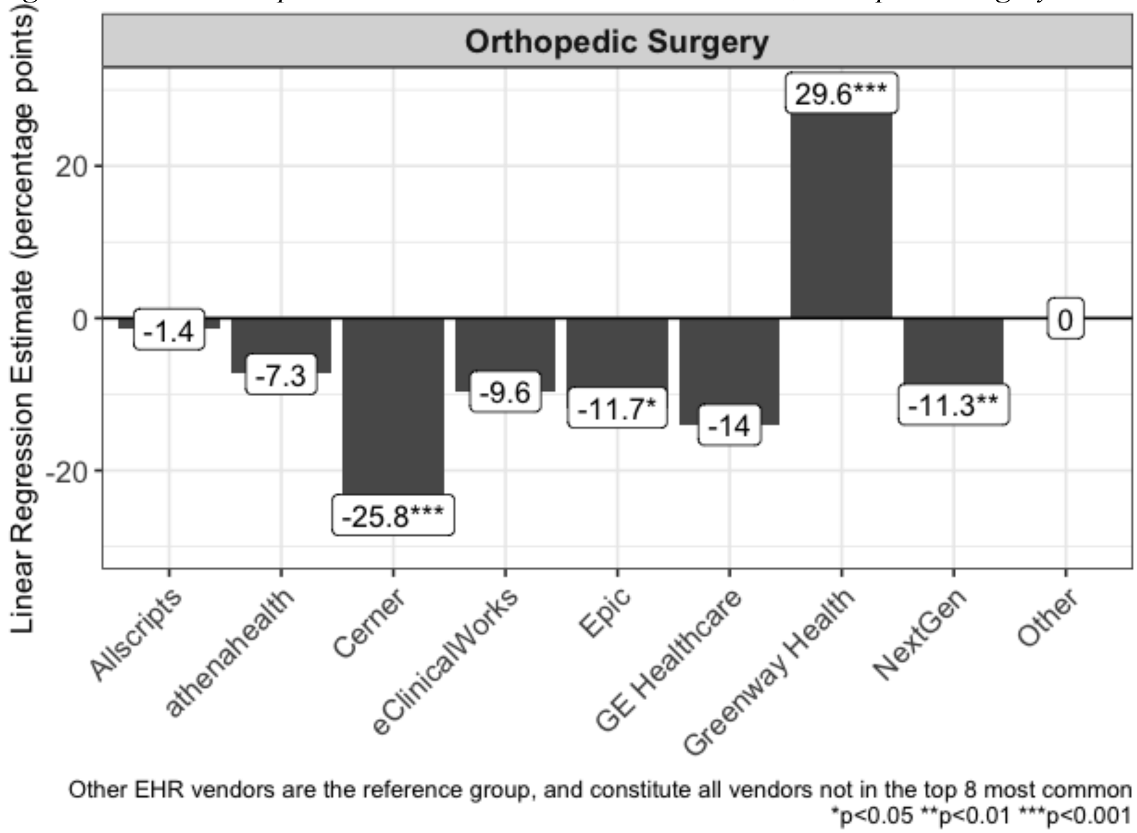
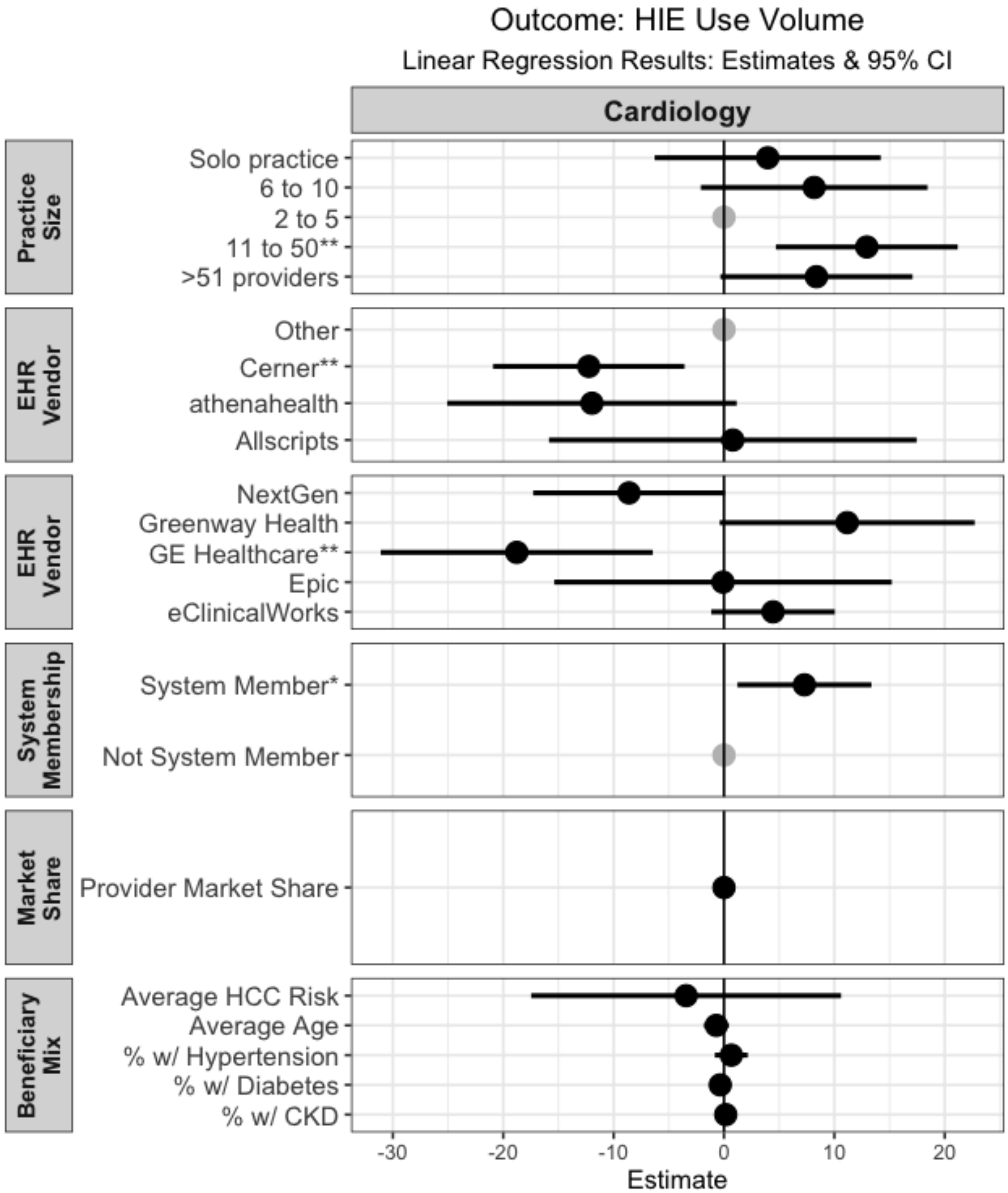
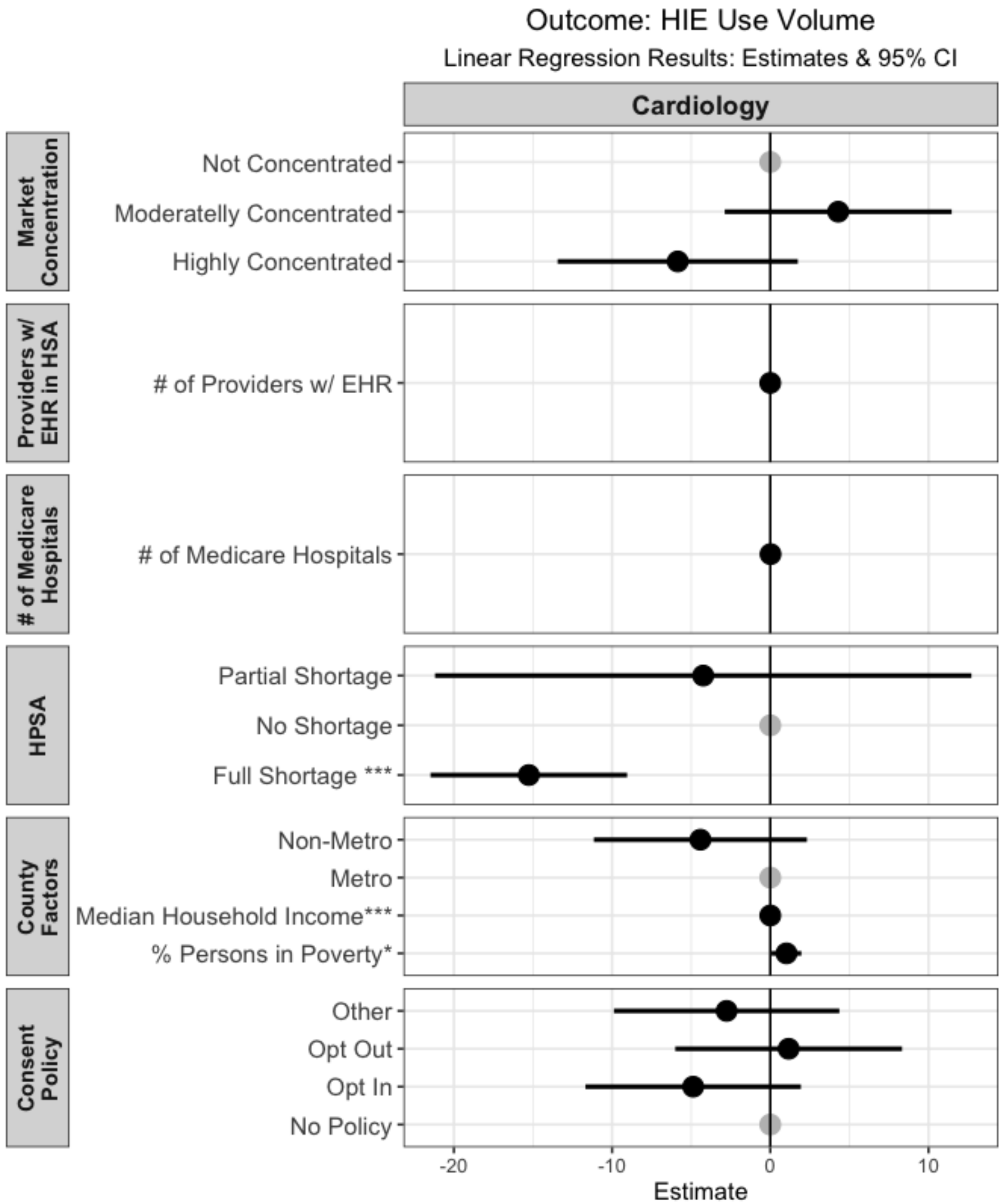


Figure A3 Practice factors associated with HIE use volume, cardiology



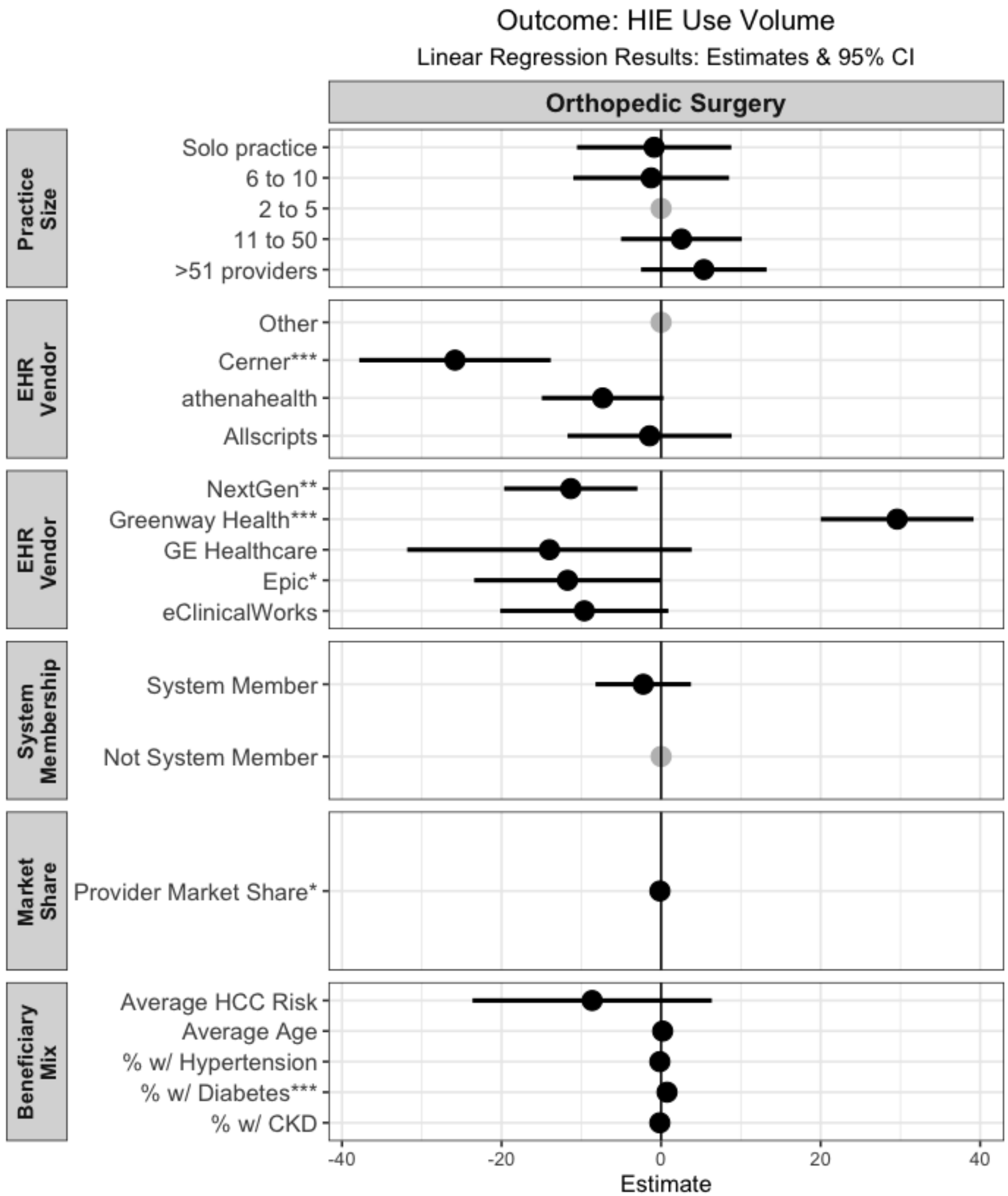
Notes: Forest plot displays results from linear regression estimates of the relationship between practice factors and provider HIE use volume. HIE use volume is measured as the percentage of referrals sent with eSCR, reported to MU Stage 2 in 2016. Model adjusts for market factors and controls for provider gender and years in practice. Significance levels: *p<0.05 **p<0.01 ***p<0.001.

Figure A4 Market factors associated with HIE use volume, cardiology



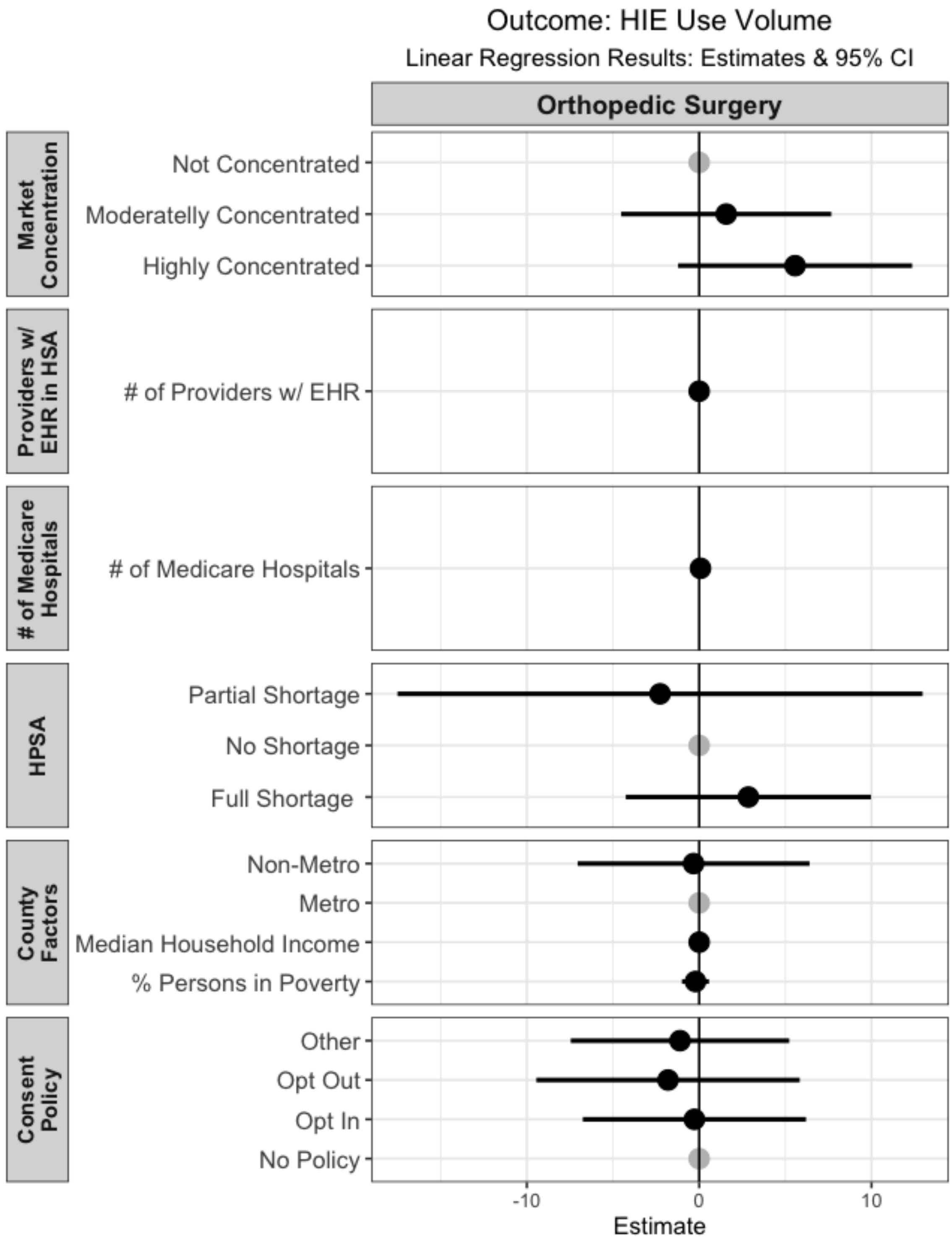
Notes: Forest plot displays results from linear regression estimates of the relationship between market factors and provider HIE use volume. HIE use volume is measured as the percentage of referrals sent with eSCR, reported to MU Stage 2 in 2016. Model adjusts for practice factors and controls for provider gender and years in practice. Significance levels: *p<0.05 **p<0.01 ***p<0.001.

Figure A5 Practice factors associated with HIE use volume, orthopedic surgery



Notes: Forest plot displays results from linear regression estimates of the relationship between practice factors and provider HIE use volume. HIE use volume is measured as the percentage of referrals sent with eSCR, reported to MU Stage 2 in 2016. Model adjusts for market factors and controls for provider gender and years in practice. Significance levels: *p<0.05 **p<0.01 ***p<0.001.

Figure A6 Market factors associated with HIE volume, orthopedic surgery



Notes: Forest plot displays results from linear regression estimates of the relationship between market factors and provider HIE use volume. HIE use volume is measured as the percentage of referrals sent with eSCR, reported to MU Stage 2 in 2016. Model adjusts for practice factors and controls for provider gender and years in practice. Significance levels: $*p<0.05$ $**p<0.01$ $***p<0.001$.

Table A2 Linear regression results, combined model controlling for provider specialty

		HIE Use Volume	
		B [95% CI]	*p-value*
Practice Factors			
Practice Size	2 to 5	reference	
	>51 providers	**4.3 [1.2,7.5]****	0.008
	11 to 50	2.2 [-0.2,4.6]	0.075
	6 to 10	-1.1 [-3.8,1.6]	0.417
	Solo practice	2.1 [-0.1,4.3]	0.064
EHR Vendor	other	reference	
	Allscripts	-3.9 [-9.1,1.2]	0.133
	athenahealth, Inc.	**17.4 [14.1,20.6]*****	p<0.001
	Cerner Corporation	**-10.1 [-15.9,-4.3]*****	p<0.001
	eClinicalWorks, LLC	**-12.2 [-15.1,-9.3]*****	p<0.001
	Epic Systems Corporation	**-7.7 [-13,-2.3]****	0.005
	GE Healthcare	**-8.6 [-13.9,-3.3]****	0.001
	Greenway Health, LLC	**15.2 [9.2,21.2]*****	p<0.001
	NextGen Healthcare	-3.2 [-7.5,1]	0.137
Health System Membership	Not in a health system	reference	
	In a health system	1.1 [-2.1,4.4]	0.497
Provider Market Share (w/in specialty)		**0.1 [0,0.2]***	0.036
Average Beneficiary Age		**0.2 [0,0.5]**	0.063
Average Beneficiary HCC Risk Score		**4.3 [1.6,7]****	0.002
% of Beneficiaries w/ CKD		**-0.2 [-0.3,0]****	0.005
% of Beneficiaries w/ Diabetes		0 [-0.1,0.2]	0.447
% of Beneficiaries w/ Hypertension		0 [-0.1,0.1]	0.674
Market Factors			
HSA Concentration Index	Unconcentrated	reference	
	Moderately Concentrated	-2 [-6,2]	0.327
	Highly Concentrated	0.2 [-3.4,3.8]	0.929
Number of Providers with EHRs in HSA		0 [0,0]	0.45
Number of Medicare Hospitals, county		**0.1 [0,0.3]***	0.014

Health Professional Shortage Area	No Shortage	reference	
	Partial Shortage	**-7.3 [-13.1,-1.4]***	0.015
	Full Shortage	**-5.4 [-8.9,-1.9]****	0.002
Median Household Income, county		0 [0,0]	0.341
Percent of Persons in Poverty, county		0.2 [-0.2,0.6]	0.288
Metro vs. Non-Metro (%)	Metro	reference	
	non-Metro	-0.3 [-3.1,2.5]	0.851
State HIE Consent Policy	NoPolicy	reference	
	OptIn	2.2 [-1.5,5.9]	0.25
	OptOut	1.2 [-1.7,4.2]	0.412
	Other	2.2 [-1,5.3]	0.176
Control Variables			
Provider Specialty	Cardiology	reference	
	Primary Care	**-19.1 [-22.6,-15.5]*****	p<0.001
	Orthopedic Surgery	**-13 [-17.7,-8.2]*****	p<0.001
Provider Gender	F	reference	
	M	-0.6 [-1.5,0.4]	0.231
Years in Practice		**0.1 [0,0.1]****	0.002
	Constant	**36.9 [14.6,59.3]****	0.001
	AIC	232615.6	
	n	24,748	

Notes: Significance levels: *p<0.05 **p<0.01 ***p<0.001.

Table A3 Heckman selection model regression results, primary care

		First Stage: HIE Exemption in 2015		Second Stage: HIE Use Volume	
		B	*se*	*B*	*se*
Practice Factors		*Heckman Selection Results*		*Heckman Selection Results*	
Practice Size	2 to 5	reference		reference	
	>51 providers	0.0916	0.064	**4.546***	1.786
	11 to 50	**0.244*****	0.0525	1.135	1.397
	6 to 10	0.0495	0.0644	-0.765	1.592
	Solo practice	**-0.170*****	0.0455	2.101	1.273
EHR Vendor	other	reference		reference	
	Allscripts	0.0128	0.088	-5.086	2.841
	athenahealth, Inc.	**0.140***	0.0679	**20.91*****	1.788
	Cerner Corporation	-0.127	0.122	**-6.605***	3.223
	eClinicalWorks, LLC	**0.313*****	0.0672	**-13.93*****	1.68
	Epic Systems Corporation	**-0.500*****	0.0935	**-6.463***	2.788
	GE Healthcare	-0.214	0.233	**-7.794***	3.26
	Greenway Health, LLC	0.0501	0.0913	**15.52*****	4.002
	NextGen Healthcare	**0.345*****	0.0967	-2.572	2.649
Health System Membership	Not in a health system	reference		reference	
	In a health system	**-0.226****	0.0736	0.253	1.872
Provider Market Share (w/in specialty)		**0.00886*****	0.00235	**0.232*****	0.0595
Average Beneficiary Age		-0.00419	0.00453	**0.341***	0.136
Average Beneficiary HCC Risk Score		**-0.314*****	0.0628	**5.462*****	1.618
% of Beneficiaries w/ CKD		-0.00302	0.00214	**-0.173****	0.0573
% of Beneficiaries w/ Diabetes		0.00248	0.00203	0.0851	0.0711
% of Beneficiaries w/ Hypertension		**0.00533***	0.00222	-0.0746	0.0642
Market Factors					
HSA Concentration Index	Unconcentrated	reference		reference	
	Moderately Concentrated	0.032	0.0873	**-4.486***	1.818

	Highly Concentrated	-0.0633	0.105	-1.727	2.948
Number of Providers with EHRs in HSA		**-0.000113***	0.0000468	0.00158	0.0024
Number of Medicare Hospitals, county		-0.000102	0.0025	**0.155***	0.0686
Health Professional Shortage Area	No Shortage	reference		reference	
	Partial Shortage	0.0417	0.105	**-7.269***	3.027
	Full Shortage	0.0996	0.0706	**-4.736***	1.896
Median Household Income, county		-0.00000259	0.00000244	-0.000000356	0.0000686
Percent of Persons in Poverty, county		-0.00192	0.00731	0.0737	0.199
Metro vs. Non-Metro (%)	Metro	reference		reference	
	non-Metro	**-0.148***	0.061	0.56	1.554
State HIE Consent Policy	NoPolicy	reference		reference	
	OptIn	0.0284	0.0617	2.563	2.127
	OptOut	-0.0556	0.0818	1.547	1.592
	Other	-0.026	0.0727	1.962	1.863
Control Variables					
Provider Gender	F	reference		reference	
	M	**0.0576****	0.0177	-0.79	0.541
Years in Practice		**-0.00622*****	0.000992	**0.0640***	0.0268
Identification Variable					
HIE Exclusion in 2015	N	reference			
	Y	**-1.725*****	0.0459		
	Constant	**1.561*****	0.385	18.39	12.13
	AIC				
	n	53,259		18,729	
	Altrho	**-0.0797081***	0.0370		
	Rho	-0.0795	0.0368		
	Lambda	-1.9673	0.9239		

Notes: Results in second stage are adjusted OLS coefficients accounting for sample selection bias modeled in first stage. All models use errors clustered at the practice level.

Significance levels: *p<0.05 **p<0.01 ***p<0.001

Table A4 Heckman selection model results, cardiology

		First Stage: HIE Exemption in 2015		Second Stage: HIE Use Volume	
		B	se	*B*	se
Practice Factors		*Heckman Selection Results*		*Heckman Selection Results*	
Practice Size	2 to 5	reference		reference	
	>51 providers	**0.368***	0.143	8.26	4.604
	11 to 50	**0.254***	0.12	**14.37*****	4.326
	6 to 10	**0.309***	0.156	10.45	5.531
	Solo practice	0.158	0.133	2.572	5.786
EHR Vendor	other	reference		reference	
	Allscripts	**-0.744*****	0.146	-1.322	9.334
	athenahealth, Inc.	**-1.152*****	0.154	**-14.74***	6.666
	Cerner Corporation	-0.111	0.162	**-13.48****	4.586
	eClinicalWorks, LLC	0.0317	0.105	5.826	3.073
	Epic Systems Corporation	**-1.638*****	0.166	-0.545	7.514
	GE Healthcare	**-0.698*****	0.177	**-22.96*****	6.254
	Greenway Health, LLC	0.0906	0.134	8.054	6.14
	NextGen Healthcare	-0.201	0.175	**-11.17***	4.671
Health System Membership	Not in a health system	reference		reference	
	In a health system	**-0.225***	0.107	**7.896****	3.046
Provider Market Share (w/in specialty)		**0.00512****	0.0018	0.084	0.0679
Average Beneficiary Age		**-0.0305***	0.0153	-0.102	0.619
Average Beneficiary HCC Risk Score		**-0.376***	0.186	-3.192	7.498
% of Beneficiaries w/ CKD		0.00765	0.00792	0.327	0.269
% of Beneficiaries w/ Diabetes		-0.0108	0.00624	-0.406	0.246
% of Beneficiaries w/ Hypertension		0.00325	0.0194	0.635	0.808
Market Factors					
HSA Concentration Index	Unconcentrated	reference		reference	

	Moderately Concentrated	0.14	0.0976	3.082	3.441
	Highly Concentrated	-0.114	0.112	-6.846	3.733
Number of Providers with EHRs in HSA		-0.0000815	0.0000795	-0.00266	0.00244
Number of Medicare Hospitals, county		0.00513	0.00346	-0.011	0.161
Health Professional Shortage Area	No Shortage	reference		reference	
	Partial Shortage	0.0512	0.22	-6.686	9.82
	Full Shortage	-0.167	0.0981	**-15.66*** **	3.07
Median Household Income, county		0.000000305	0.0000051	**0.000359*** **	0.000104
Percent of Persons in Poverty, county		-0.00613	0.0134	0.904	0.473
Metro vs. Non-Metro (%)	Metro	reference		reference	
	non-Metro	0.046	0.0974	-4.864	3.488
State HIE Consent Policy	NoPolicy	reference		reference	
	OptIn	**0.184***	0.09	-4.157	3.588
	OptOut	-0.136	0.111	0.138	3.706
	Other	0.134	0.123	-3.35	3.83
Control Variables					
Provider Gender	F	reference		reference	
	M	0.0306	0.0666	0.855	2.484
Years in Practice		**-0.00417***	0.00209	0.115	0.065
Identification Variable					
HIE Exclusion in 2015	N	reference			
	Y	**-1.825*** **	0.0758		
	Constant	3.424	1.817	-1.212	75.42
	AIC				
	n	17,478		1,925	
	Altrho	0.01547	0.0592		
	Rho	0.01547	0.0592		
	Lambda	0.42806	1.63968		

Notes: Results in second stage are adjusted OLS coefficients accounting for sample selection bias modeled in first stage. All models use errors clustered at the practice level. Significance levels: *p<0.05 **p<0.01 ***p<0.001

Table A5 Heckman selection model results, orthopedic surgery

		First Stage: HIE Exemption in 2015		Second Stage: HIE Use Volume	
		B	se	*B*	se
Practice Factors		*Heckman Selection Results*		*Heckman Selection Results*	
Practice Size	2 to 5	reference		reference	
	>51 providers	-0.097	0.154	6.284	4.33
	11 to 50	-0.163	0.138	4.835	4.035
	6 to 10	-0.328	0.203	0.614	5.183
	Solo practice	-0.0543	0.165	1.102	5.212
EHR Vendor	other	reference		reference	
	Allscripts	**0.509***	0.211	-1.432	5.472
	athenahealth, Inc.	**0.804*****	0.108	-5.685	4.238
	Cerner Corporation	-0.258	0.249	**-21.88****	7.739
	eClinicalWorks, LLC	**0.606*****	0.164	-10.45	6.029
	Epic Systems Corporation	**-0.421****	0.15	**-17.83****	6.501
	GE Healthcare	0.000934	0.176	**-21.25***	8.952
	Greenway Health, LLC	0.23	0.175	**29.07*****	5.341
	NextGen Healthcare	**0.425***	0.206	**-11.84***	4.657
Health System Membership	Not in a health system	reference		reference	
	In a health system	-0.127	0.138	-0.669	3.384
Provider Market Share (w/in specialty)		0.00339	0.00188	**-0.154****	0.0596
Average Beneficiary Age		-0.0217	0.0145	0.234	0.51
Average Beneficiary HCC Risk Score		**-0.680****	0.208	-12.46	8.235
% of Beneficiaries w/ CKD		0.0151	0.00951	0.00666	0.304
% of Beneficiaries w/ Diabetes		0.00119	0.00771	**0.634****	0.245
% of Beneficiaries w/ Hypertension		0.00488	0.0085	-0.12	0.227
Market Factors					
HSA Concentration Index	Unconcentrated	reference		reference	
	Moderately Concentrated	0.0458	0.106	3.089	3.218

	Highly Concentrated	-0.0379	0.129	6.046	3.54
Number of Providers with EHRs in HSA		0.000106	0.000164	0.00129	0.00248
Number of Medicare Hospitals, county		-0.00992	0.00664	-0.0731	0.146
Health Professional Shortage Area	No Shortage	reference		reference	
	Partial Shortage	-0.201	0.251	3.371	9.175
	Full Shortage	0.0252	0.126	4.438	3.702
Median Household Income, county		-0.00000653	0.00000607	**0.000302***	0.000137
Percent of Persons in Poverty, county		-0.0157	0.0191	0.101	0.376
Metro vs. Non-Metro (%)	Metro	reference		reference	
	non-Metro	0.0372	0.117	0.932	3.567
State HIE Consent Policy	NoPolicy	reference		reference	
	OptIn	0.2	0.143	0.102	3.405
	OptOut	-0.17	0.108	0.701	4.023
	Other	0.0675	0.121	0.339	3.344
Control Variables					
Provider Gender	F	reference		reference	
	M	0.125	0.129	-2.849	5.242
Years in Practice		-0.00221	0.00218	-0.0616	0.0849
Identification Variable					
HIE Exclusion in 2015	N	reference			
	Y	**-1.879*****	0.0998		
	Constant	**2.501***	1.107	24.08	41.76
	AIC				
	n	8,757		1,271	
	Altrho	-0.025255	0.0737		
	Rho	-0.0252496	0.0736		
	Lambda	-0.6424535	1.8698		

Notes: Results in second stage are adjusted OLS coefficients accounting for sample selection bias modeled in first stage. All models use errors clustered at the practice level. Significance levels: *p<0.05 **p<0.01 ***p<0.001.

Appendix B: Chapter 3 Supplemental Materials

Rochester RHIO Background, Workflow, and Use Data

Note: Reference numbers refer to reference list at the end of Chapter 3.

After major state investment to build a statewide HIE network, the Rochester RHIO query portal services became operational in 2008 [38]. The secure web portal allows for authorized, RHIO-approved physicians and other clinical staff members to access patient health information contributed from health organizations [19]. Data is provided to the Rochester RHIO database by hospitals, laboratories, physician offices, public health agencies, home health centers, and payers in the 13-county service region [39]. During the study period, the Rochester RHIO contained information on more than 1 million patients [19], from more than 100 data-contributing organizations [39]. More than two-thirds of the hospitals and physician practices in the Rochester region participated in the exchange during this time [13,40]. The health information available to providers includes admission, discharge, and transfer (ADT) documents, diagnoses, vital sign results, radiology reports and images, medication history, laboratory results, and information from insurance companies [13,30,39,40].

The user workflow to query the RHIO involves several steps. Upon logging in to the web-based query portal, users search for a patient and confirm that the patient has consented to data sharing. More than 97 percent of patients consent to information exchange [19], a very high rate consistent with other opt-in consent settings in regional health information organizations [21]. For consented patients, the user is brought to a page with tabbed sections of patient health information [41]. The default landing section is the Patient Summary section, which includes aggregated information on the patient's most recent laboratory orders, radiology studies, clinical notes from outside visits, and ADT documents. Users can then navigate to section tabs for Laboratory, Radiology, ADT, Reports, and Vital Signs. These sections aggregate individual test results and reports for summative views, and make individual results available for more detailed exploration by the user, who can then open specific results or documents to view more information and context. We exploit these two levels of use (section viewing and specific document viewing) in our measurements of use breadth and depth. Users are only able to access a single patient record at a time, and must return to the initial query page to search for additional patients [30].

The Rochester RHIO provided detailed logs of all exchange query portal use from users at the PCMHs between January 2012 and December 2015. This dataset includes 241 unique users and 5.2 million observations of discrete “events” in the portal for 24,421 unique patients during this timeframe. An “event” is logged for each click within the HIE, including clicks on the patient search page, clicks when viewing the patient health record summary, and clicks to navigate within the HIE. Each click observation includes the page of the portal on which that click took place, allowing for identification of the section or document type a user accessed while using the HIE. This data also includes the specific time of the event, the user identifier, and an anonymized patient identifier for linking with visit data from the EHR, described below. The data also included the user role in the clinic, listed as one of seven possible types: physician, nurse midwife or RN, nurse practitioner, care manager, licensed health professional (primarily licensed clinical social workers), a midlevel provider (primarily physician assistants), or staff. A minority of users had no user type listed and were classified as “unknown.”

Table B1 Information categories in HIE use data by volume

Information Category	# of Actions
Summary Section	80635
Laboratory Result Document	14433
Laboratory Section	12617
Reports Section	7008
Clinical Result Document	6855
Radiology Result Document	6430
Unclassified	6163
Radiology Section	5006
Patient Index Document	4152
Transcriptions Section	3952
ADT Document	2959
ADT Section	746
Vitals Section	429
Emergency Document	58
Unclassified Result Document	21

Table B2 Encounter diagnoses classified via AHRQ CCS Algorithm

Chronic Disease Classifications	**Other Disease Classifications**
Asthma Cancer Chronic Obstructive Pulmonary Disorder (COPD) Congestive Heart Failure Coronary Artery Disease Diabetes Hyperlipidemia Hypertension	Arthritis Cardiac Arrest Depression Drug-related primary diagnosis Hepatitis Human Immunodeficiency Virus (HIV) Injury-related visit Osteoporosis Schizophrenia Stroke

Table B3 Descriptive statistics of visit sample, stratified by HIE use timing relative to visit

	Overall	**Two Weeks Prior**	**Same Day**	**Two Weeks After**	p
Number of Visits	12556	4668	4322	4624	
HIE Use Breadth***	n/a	5.62 (2.30)	6.07 (2.17)	5.46 (2.17)	<0.001
HIE Use Depth***	n/a	31.51 (34.48)	33.59 (32.86)	29.46 (34.07)	<0.001
Team-Based HIE Use***					
No	1854 (14.8)	556 (11.9)	906 (21.0)	651 (14.1)	<0.001
Yes	10702 (85.2)	4112 (88.1)	3416 (79.0)	3973 (85.9)	
Number of HIE Users*** (mean, sd)	n/a	1.06 (0.26)	1.02 (0.16)	1.06 (0.26)	<0.001
Patient Sex					
Female	8080 (64.4)	2982 (63.9)	2823 (65.3)	2986 (64.6)	0.364
Male	4476 (35.6)	1686 (36.1)	1499 (34.7)	1638 (35.4)	
Patient Age @ Visit (mean, sd)	46.22 (15.35)	46.11 (15.20)	46.15 (15.06)	46.48 (15.67)	0.448
Chronic Primary Diagnosis*					
No	10373 (82.6)	3888 (83.3)	3519 (81.4)	3849 (83.2)	0.03
Yes	2183 (17.4)	780 (16.7)	803 (18.6)	775 (16.8)	
Visit Duration***					
<15mins	11 (0.1)	8 (0.2)	1 (0.0)	4 (0.1)	<0.001
15mins	5329 (42.4)	1988 (42.6)	1688 (39.1)	2053 (44.4)	
20mins	1931 (15.4)	734 (15.7)	749 (17.3)	572 (12.4)	
30mins	4469 (35.6)	1639 (35.1)	1615 (37.4)	1668 (36.1)	
45mins	453 (3.6)	122 (2.6)	181 (4.2)	181 (3.9)	
60mins	341 (2.7)	166 (3.6)	85 (2.0)	135 (2.9)	
>1hr	22 (0.2)	11 (0.2)	3 (0.1)	11 (0.2)	
Days Since Visit Scheduled***					
>3mo prior	197 (1.6)	69 (1.5)	61 (1.4)	80 (1.7)	<0.001
3mo prior	634 (5.1)	235 (5.0)	210 (4.9)	234 (5.1)	

Month prior	1645 (13.1)	552 (11.8)	563 (13.0)	668 (14.4)	
Two weeks prior	2075 (16.5)	855 (18.3)	663 (15.4)	745 (16.1)	
Week prior	3512 (28.0)	1405 (30.1)	1309 (30.3)	1136 (24.6)	
Day prior	1554 (12.4)	507 (10.9)	650 (15.1)	510 (11.0)	
Same day	2825 (22.5)	988 (21.2)	844 (19.5)	1208 (26.1)	
Recorded After Visit	108 (0.9)	56 (1.2)	18 (0.4)	42 (0.9)	
Days Since Last Visit***					
No Past Visit	1703 (13.6)	440 (9.4)	700 (16.2)	690 (14.9)	<0.001
> 1yr	210 (1.7)	44 (0.9)	85 (2.0)	91 (2.0)	
Previous 1yr	480 (3.8)	110 (2.4)	198 (4.6)	197 (4.3)	
Previous 6mo	1038 (8.3)	264 (5.7)	427 (9.9)	424 (9.2)	
Previous 90d	2499 (19.9)	752 (16.1)	1006 (23.3)	919 (19.9)	
Previous 1mo	6626 (52.8)	3058 (65.5)	1906 (44.1)	2303 (49.8)	
Year***					
2012	2937 (23.4)	1054 (22.6)	1148 (26.6)	933 (20.2)	<0.001
2013	2548 (20.3)	959 (20.5)	747 (17.3)	1008 (21.8)	
2014	4106 (32.7)	1494 (32.0)	1373 (31.8)	1655 (35.8)	
2015	2965 (23.6)	1161 (24.9)	1054 (24.4)	1028 (22.2)	
Site ***					
AJHC	9134 (72.7)	3117 (66.8)	3474 (80.4)	3208 (69.4)	<0.001
OOCHC	2068 (16.5)	1101 (23.6)	140 (3.2)	989 (21.4)	
RPCN	1354 (10.8)	450 (9.6)	708 (16.4)	427 (9.2)	

Notes: All values are counts with percentages in parenthesis unless otherwise noted. P-values show the results of a chi-squared goodness of fit test for differences across the three timing categories. Significance levels: *p<0.05 **p<0.01 ***p<0.001.

Table B4 Negative binomial regression results: HIE use breadth

	Outcome: HIE Use Breadth (count of unique information categories viewed)					
	Two Weeks Prior		Same Day		Two Weeks After	
	beta [95% CI]	*p-value*	*beta [95% CI]*	*p-value*	*beta [95% CI]*	*p-value*
Team-Based HIE Use						
No	Reference		Reference		Reference	
Yes	0.034 [-0.01,0.07]	0.1015	0.033 [0,0.07]	0.0667	-0.009 [-0.05,0.03]	0.629
Number of HIE Users	**0.259 [0.22,0.3]**	<0.001	**0.283 [0.22,0.35]**	<0.001	**0.291 [0.25,0.33]**	<0.001
Patient Sex						
Female	Reference		Reference		Reference	
Male	**0.033 [0.01,0.06]**	0.0136	0.014 [-0.01,0.04]	0.3142	0.009 [-0.02,0.04]	0.5069
Patient Age @ Visit	-0.001 [0,0]	0.1242	0.000 [0,0]	0.7274	0.000 [0,0]	0.6612
Chronic Primary Diagnosis						
No	Reference		Reference		Reference	
Yes	0.004 [-0.03,0.04]	0.7976	-0.018 [-0.05,0.01]	0.2819	-0.008 [-0.04,0.03]	0.6659
Visit Duration						
<15mins	-0.005 [-0.3,0.29]	0.971	0.425 [-0.2,1.05]	0.1805	-0.057 [-0.48,0.36]	0.7887
15mins	**-0.049 [-0.08,-0.02]**	0.0016	**-0.089 [-0.12,-0.06]**	<0.001	**-0.048 [-0.08,-0.02]**	0.002
20mins	-0.025 [-0.07,0.02]	0.2345	0.022 [-0.02,0.06]	0.2643	0.041 [0,0.09]	0.0683
30mins	Reference		Reference		Reference	
45mins	0.005 [-0.07,0.08]	0.896	0.031 [-0.03,0.09]	0.3286	-0.004 [-0.07,0.06]	0.9169
60mins	0.020 [-0.05,0.09]	0.5872	-0.020 [-0.11,0.07]	0.6766	-0.006 [-0.08,0.07]	0.8888
>1hr	-0.012 [-0.26,0.24]	0.9268	-0.105 [-0.59,0.38]	0.67	0.192 [-0.02,0.41]	0.0782
Days Since Visit Scheduled						
>3mo prior	-0.070 [-0.18,0.04]	0.2313	-0.035 [-0.15,0.08]	0.5424	0.048 [-0.06,0.15]	0.3739
3mo prior	**-0.068 [-0.14,0]**	0.0471	-0.041 [-0.11,0.03]	0.2275	0.052 [-0.02,0.12]	0.1298
Month prior	**-0.110 [-0.16,-0.06]**	<0.001	**-0.052 [-0.1,0]**	0.0317	-0.024 [-0.07,0.03]	0.3606
Two weeks prior	-0.030 [-0.08,0.02]	0.2013	0.000 [-0.04,0.04]	0.9912	-0.002 [-0.05,0.05]	0.9388
Week prior	-0.025 [-0.07,0.02]	0.2449	-0.009 [-0.05,0.03]	0.6332	0.012 [-0.03,0.06]	0.6073
Day prior	Reference		Reference		Reference	

Same day	**-0.064 [-0.11,-0.02]**	0.0057	-0.016 [-0.06,0.03]	0.4467	**0.048 [0,0.09]**	0.0327
Recorded After Visit	**-0.125 [-0.24,-0.01]**	0.0371	-0.178 [-0.38,0.03]	0.0915	0.007 [-0.13,0.14]	0.9241
Days Since Last Visit						
No Past Visit	-0.084 [-0.22,0.05]	0.2223	0.006 [-0.09,0.1]	0.9005	0.053 [-0.05,0.15]	0.2896
> 1yr	Reference		Reference		Reference	
Previous 1yr	-0.007 [-0.16,0.14]	0.9228	-0.034 [-0.14,0.07]	0.5115	0.061 [-0.05,0.17]	0.2762
Previous 6mo	-0.013 [-0.15,0.12]	0.8546	-0.057 [-0.15,0.04]	0.2337	0.031 [-0.07,0.13]	0.5523
Previous 90d	-0.042 [-0.17,0.09]	0.527	-0.051 [-0.14,0.04]	0.2637	0.059 [-0.04,0.16]	0.2297
Previous 1mo	-0.005 [-0.13,0.12]	0.9405	-0.054 [-0.14,0.03]	0.2252	0.063 [-0.03,0.16]	0.1891
Year						
2012	Reference		Reference		Reference	
2013	**-0.115 [-0.15,-0.08]**	<0.001	0.034 [-0.01,0.07]	0.0905	**-0.126 [-0.17,-0.09]**	<0.001
2014	**-0.061 [-0.09,-0.03]**	<0.001	0.010 [-0.02,0.04]	0.5728	**-0.084 [-0.12,-0.05]**	<0.001
2015	**-0.070 [-0.11,-0.03]**	<0.001	-0.016 [-0.05,0.02]	0.4006	**-0.088 [-0.13,-0.05]**	<0.001
Site						
AJHC	Reference		Reference		Reference	
OOCHC	**-0.250 [-0.29,-0.21]**	<0.001	-0.347 [-0.43,-0.27]	<0.001	**-0.223 [-0.26,-0.19]**	<0.001
RPCN	**0.111 [0.07,0.15]**	<0.001	0.045 [0,0.09]	0.0292	**0.119 [0.07,0.16]**	<0.001
Intercept	**1.625 [1.47,1.78]**	<0.001	**1.575 [1.45,1.7]**	<0.001	**1.433 [1.31,1.56]**	<0.001

Notes: Bold estimates are statistically significant at the p<0.05 level.

Table B5 Linear regression results: HIE use depth

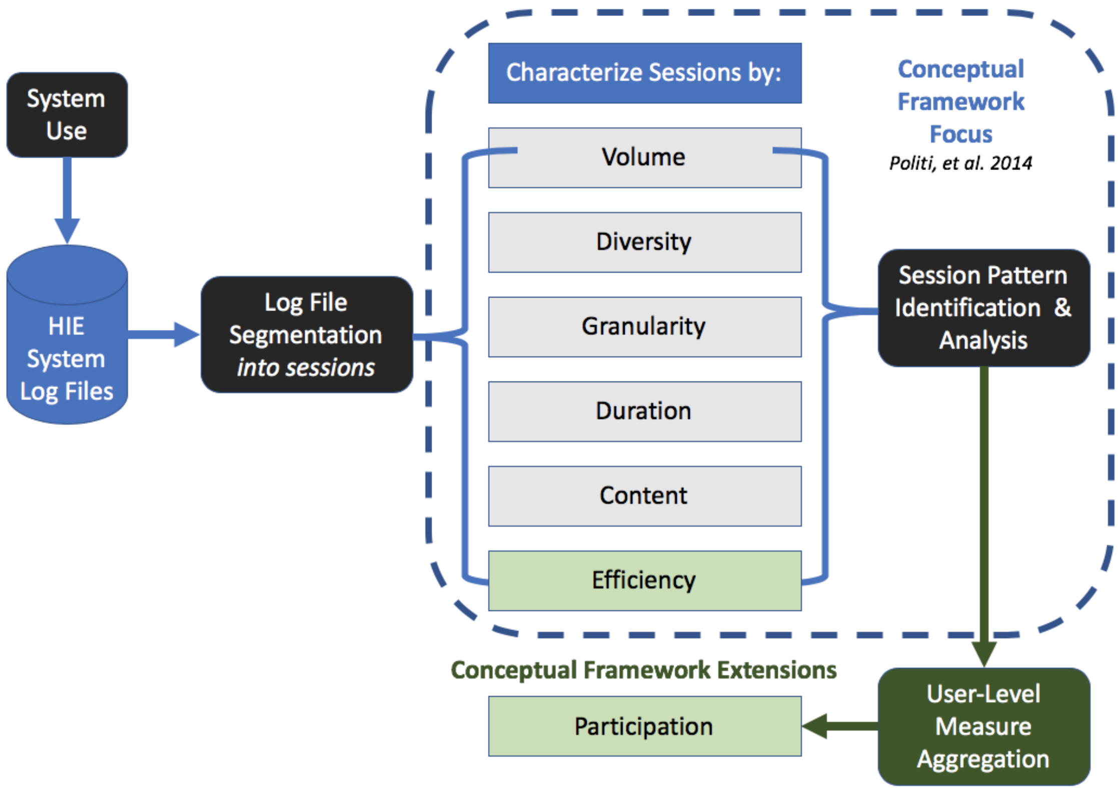
	Outcome: HIE Use Depth (percentage of action spent viewing specific documents)					
	Two Weeks Prior		Same Day		Two Weeks After	
	beta [95% CI]	*p-value*	*beta [95% CI]*	*p-value*	*beta [95% CI]*	*p-value*
Team-Based HIE Use						
No	Reference		Reference		Reference	
Yes	**-4.20 [-7.6,-0.8]**	0.0142	-2.65 [-5.6,0.3]	0.0759	**-5.81 [-8.9,-2.7]**	p<0.001
Number of HIE Users	-2.61 [-6.5,1.3]	0.1881	**-7.53 [-13.8,-1.3]**	0.0186	-0.97 [-4.8,2.9]	
Patient Sex						
Female	Reference		Reference			
Male	**4.00 [1.8,6.2]**	<0.001	0.62 [-1.6,2.8]	0.5797	**2.77 [0.6,5]**	0.0142
Patient Age @ Visit	-0.07 [-0.1,0]	0.0564	-0.03 [-0.1,0]	0.3686	-0.02 [-0.1,0.1]	0.5813
Chronic Primary Diagnosis						
No	Reference		Reference		Reference	
Yes	-0.77 [-3.7,2.1]	0.6040	-0.26 [-3,2.5]	0.8513	-1.99 [-4.9,0.9]	0.1834
Visit Duration						
<15mins	-5.64 [-33.2,21.9]	0.6885	-28.24 [-92.4,35.9]	0.3885	-26.82 [-65.2,11.6]	0.1712
15mins	-0.41 [-3,2.2]	0.7526	-2.35 [-4.8,0.2]	0.0657	-0.57 [-3.1,2]	0.6568
20mins	0.37 [-3.2,3.9]	0.8375	-1.51 [-4.7,1.7]	0.3612	1.22 [-2.5,5]	0.5256
30mins	Reference		Reference		Reference	
45mins	-1.22 [-7.9,5.5]	0.7214	-1.08 [-6.4,4.3]	0.6913	-0.48 [-6,5]	0.8652
60mins	**7.15 [1.1,13.2]**	0.0200	-1.52 [-9.1,6.1]	0.6949	**7.57 [1.2,13.9]**	0.0194
>1hr	7.53 [-13.7,28.8]	0.4874	-19.04 [-56.5,18.5]	0.3197	0.28 [-20.9,21.5]	0.9793
Days Since Visit Scheduled						
>3mo prior	0.08 [-9.3,9.5]	0.9872	**-9.35 [-18.7,0]**	0.0497	**-8.92 [-17.6,-0.2]**	0.0450
3mo prior	-3.36 [-9.1,2.4]	0.2495	**-7.61 [-13.1,-2.1]**	0.0066	**-8.41 [-14.1,-2.8]**	0.0036
Month prior	-0.94 [-5.4,3.5]	0.6777	-2.57 [-6.5,1.3]	0.1979	**-5.58 [-9.8,-1.4]**	0.0093
Two weeks prior	3.19 [-0.8,7.2]	0.1151	-2.85 [-6.6,0.9]	0.1315	**-4.84 [-8.9,-0.8]**	0.0197
Week prior	2.70 [-1,6.3]	0.1476	1.18 [-2,4.4]	0.4667	-0.18 [-3.9,3.6]	0.9249
Day prior	Reference		Reference		Reference	

Same day	1.76 [-2.1,5.6]	0.3721	2.86 [-0.6,6.3]	0.1046	-2.31 [-6,1.4]	0.2231
Recorded After Visit	**17.05 [7.2,26.9]**	p<0.001	15.29 [-0.2,30.8]	0.0535	-10.35 [-21.6,0.9]	0.0708
Days Since Last Visit						
No Past Visit	3.12 [-7.9,14.2]	0.5798	0.23 [-7.6,8]	0.9539	7.84 [-0.7,16.4]	0.0710
> 1yr	Reference		Reference		Reference	
Previous 1yr	-2.46 [-14.8,9.9]	0.6959	-0.33 [-8.9,8.3]	0.9408	8.10 [-1.4,17.6]	0.0932
Previous 6mo	-7.93 [-19.2,3.3]	0.1670	4.11 [-3.8,12]	0.3100	7.16 [-1.6,15.9]	0.1092
Previous 90d	-7.49 [-18.2,3.2]	0.1699	2.42 [-5.1,10]	0.5307	6.96 [-1.4,15.3]	0.1031
Previous 1mo	-3.61 [-14.1,6.9]	0.5006	1.11 [-6.3,8.5]	0.7704	6.57 [-1.6,14.8]	0.1156
Year						
2012	Reference		Reference		Reference	
2013	**-6.74 [-10,-3.5]**	<0.001	-2.92 [-6.2,0.3]	0.0776	**-7.01 [-10.3,-3.7]**	<0.001
2014	0.30 [-2.6,3.2]	0.8419	**-4.29 [-7.1,-1.5]**	0.0030	-2.39 [-5.3,0.5]	0.1111
2015	-1.72 [-4.9,1.4]	0.2841	**-3.59 [-6.6,-0.5]**	0.0214	-1.31 [-4.6,2]	0.4404
Site						
AJHC	Reference		Reference		Reference	
OOCHC	-2.61 [-5.8,0.6]	0.1089	-2.03 [-8.1,4]	0.5128	2.77 [-0.1,5.6]	0.0577
RPCN	**-4.88 [-8.7,-1]**	0.0132	**-5.23 [-8.6,-1.9]**	0.0023	-2.12 [-6,1.8]	0.2877
Intercept	**44.55 [31.9,57.2]**	p<0.001	**48.52 [37.6,59.5]**	p<0.001	**33.89 [23.2,44.5]**	p<0.001

Notes: Bold estimates are significant at the p<0.05 level.

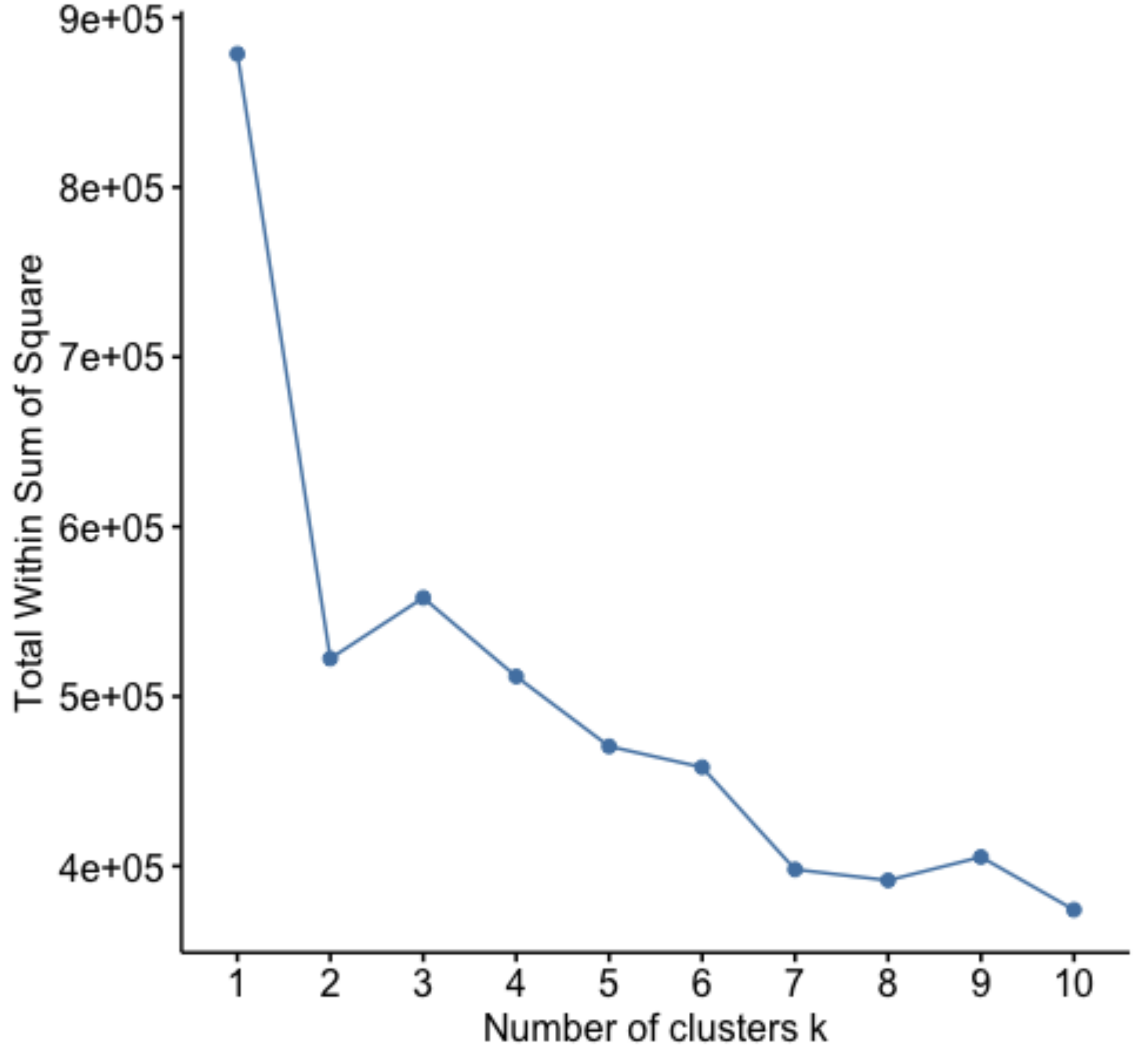
Appendix C: Chapter 4 Supplemental Materials

Figure C1 Conceptual framework for measuring multidimensional use patterns of HIE



Notes: Original framework focus is replicated from [7], green portions denote framework extensions for the purposes of this study.

Figure C2 Scree plot of within-sum-of-squares error at values of k=1 through k=10



Scree plot of within-sum-of-squares model fit statistic illustrating optimal number of clusters for CLARA clustering model using PAM algorithm, k=1 through k=10. The location of the "elbow" or initial flattening of the slope of the line at k=5 suggests that the optimal number of clusters that does not overfit the data is 5.

Table C1 HIE use measure correlation matrix, Regulars

		Volume		***Diversity***	***Granularity***	***Duration***	***Content***					***Efficiency***	
		# of Actions per Session	# of Patients per Session	# of Information Categories Viewed	% of Clinical Actions on Reports	Session Duration (mins)	Summary Pages	Lab Content	Radiology Content	Vitals Content	ADT Content	% of Activity Outside Patient Record	% of Outside Activity: Login
Volume	# of Patients per Session	0.87											
Diversity	# of Information Categories Viewed	0.43	0.24										
Granularity	Proportion of Clinical Actions on Reports	0.12	0.06	0.35									
Duration	Session Duration (mins)	0.77	0.74	0.23	0.06								
Content	Summary Pages (count of actions)	0.90	0.75	0.39	0.00	0.60							
Content	Lab Content (count of actions)	0.45	0.29	0.44	0.29	0.39	0.30						
Content	Radiology Content (count of actions)	0.22	0.06	0.49	0.21	0.11	0.16	0.24					
Content	Vitals Content (count of actions)	0.18	0.05	0.21	0.44	0.09	0.11	0.04	0.07				
Content	ADT Content (count of actions)	0.28	0.15	0.43	0.15	0.11	0.31	0.13	0.21	0.14			
Efficiency	% of Activity Outside Patient Record	-0.31	-0.30	-0.66	-0.33	-0.13	-0.28	-0.35	-0.28	-0.11	-0.21		
Efficiency	% of Outside Activity: Login	-0.26	-0.21	-0.24	-0.10	-0.20	-0.24	-0.12	-0.09	-0.07	-0.06	0.09	
Efficiency	% of Outside Activity: Patient Search	-0.02	0.09	-0.03	-0.05	0.05	-0.06	0.02	-0.02	-0.06	-0.01	-0.31	-0.10

Table C2 HIE use measure correlation matrix, Browsers

		Volume		*Diversity*	*Granularity*	*Duration*			*Content*			*Efficiency*	
		# of Actions per Session	# of Patients per Session	# of Information Categories Viewed	% of Clinical Actions on Reports	Session Duration (mins)	Summary Pages	Lab Content	Radiology Content	Vitals Content	ADT Content	% of Activity Outside Patient Record	% of Outside Activity: Login
Volume	# of Patients per Session	0.67											
Diversity	# of Information Categories Viewed	0.66	0.51										
Granularity	% of Clinical Actions on Reports	0.32	0.21	0.38									
Duration	Session Duration (mins)	0.54	0.33	0.23	0.14								
Content	Summary Pages (count of actions)	0.81	0.59	0.65	0.15	0.24							
Content	Lab Content (count of actions)	0.34	0.19	0.36	0.27	0.12	0.30						
Content	Radiology Content (count of actions)	0.31	0.16	0.42	0.18	0.06	0.34	0.11					
Content	Vitals Content (count of actions)	0.37	0.03	0.08	0.37	0.11	0.03	0.01	0.02				
Content	ADT Content (count of actions)	0.29	0.17	0.54	0.20	0.10	0.34	0.08	0.15	0.04			
Efficiency	% of Activity Outside Patient Record	-0.51	-0.62	-0.73	-0.33	-0.09	-0.56	-0.33	-0.32	-0.02	-0.29		
Efficiency	% of Outside Activity: Login	-0.32	-0.24	-0.30	-0.14	-0.15	-0.29	-0.09	-0.04	-0.07	-0.10	0.16	
Efficiency	% of Outside Activity: Patient Search	-0.01	0.10	0.03	-0.17	0.06	-0.05	-0.02	-0.01	-0.07	-0.05	-0.22	-0.32

Curriculum Vitae

Nathan Calvert Apathy

Education

PhD, Health Policy & Management
Indiana University Richard M. Fairbanks School of Public Health at IUPUI, 2020
Indianapolis, IN

BS, Business Administration (Economics)
Creighton University, 2011
Omaha, NE

Professional Experience

Cerner Corporation, 2011-2016
Kansas City, MO

- Program Manager, Southcentral Foundation Innovation Collaborative, 2015-2016
- Product Manager, Research Software, 2013-2016
- Solution Architect, General Laboratory Software, 2011-2013

Research Experience

Graduate Research Assistant to Christopher A. Harle, PhD, 2016-2020

- Nudging Primary Care Providers Toward Guideline-Recommended Opioid Prescribing Through Easier & More Convenient EHR Information Design
    - R21DA046085-03 & R33DA046085-03

Fellowships

Predoctoral Fellowship in Public & Population Health Informatics, IUPUI, 2017-2020

- The Indiana Training Program in Public & Population Health Informatics
    - T15LM012502-03

University Graduate Fellowship, IUPUI, 2016

Peer-Reviewed Publications

Holmgren, AJ; Apathy, NC; Adler-Milstein, J. Barriers to Hospital Public Health Reporting and Implications for the COVID-19 Pandemic. Journal of the American Medical Informatics Association. May 2020.

Apathy, NC; Harle, CA; Vest, JR; Morea, JG; Menachemi, N. Use of electronic health records on days off: Comparing physicians to other EHR users. In Press, Journal of General Internal Medicine.

Apathy, NC; Everson, J. High rates of partial participation in the first year of the Merit-Based Incentive Program. Accepted, Health Affairs.

Holmgren, AJ; Apathy, NC. Prescription drug monitoring program integration with hospital EHRs is low, especially in high opioid prescribing areas. In Press, JAMA Network Open.

Apathy, NC; Holmgren, AJ. Opt-in consent policies: potential barriers to hospital health information exchange. American Journal of Managed Care. 2020;26(1).

Holmgren, AJ; Apathy, NC. Hospital adoption of API-enabled patient data access. Healthcare: The Journal of Delivery Science and Innovation. 2019;8.

Balio, CP; Apathy, NC; Danek, R. Health information technology and accountable care organizations: synthesis of the literature and future directions. eGEMs (Generating Evidence & Methods to improve patient outcomes). 2019;7(1):24.

Apathy NC; Yeager VA. Examining Training Motivations Among Public Health Workers. Journal of Public Health Management and Practice. 2019;25(2), Public Health Workforce Interests and Needs Survey 2017: S157–65.

Harle, CA; Apathy, NC; Cook, RL; Danielson, EC; DiIulio, J; Downs, SM; Hurley, RW; Mamlin, BW; Militello, LG; Anders, S. Information Needs and Requirements for Decision Support in Primary Care: An Analysis of Chronic Pain Care. AMIA Annual Symposium Proceedings. 2018 Nov.

Apathy, NC; Menser, T; Keeran, L; Ford, EW; Harle, CA; Huerta, TR. Trends and gaps in awareness of direct-to-consumer genetic tests from 2007-2014. American Journal of Preventive Medicine. 2018 Jun 1;54(6):806-13.

Mosa, AS; Yoo, I; Apathy, NC; Ko, KJ; Parker, JC. Secondary Use of Clinical Data to Enable Data-Driven Translational Science with Trustworthy Access Management. Missouri Medicine. 2015;112(6):443-448.

Book Chapters

Dixon, BE; Rahurkar, S; & Apathy, NC. Health Information Exchange. In: Magnuson, JA; Dixon, BE, editors. Public Health Informatics and Information Systems, 3rd edition. Springer London. Under development, publication 2020.

Editorial Experience

American Journal of Managed Care, Peer Reviewer
Journal of General Internal Medicine, Peer Reviewer
International Conference on Information Systems, Conference Submission Review
AcademyHealth Annual Research Meeting, Theme Reviewer & Session Chair
- Digital Technologies, Data, and Data Science Theme

Journal of the American Medical Informatics Association (JAMIA), Peer Review
AMIA Annual Symposium, Conference Submission Review
AMIA Informatics Summits, Conference Submission Review

Professional Memberships

American Public Health Association, 2019 –
AcademyHealth, 2016 –
Health Information & Management Systems Society (HIMSS), 2016 –
American Medical Informatics Association (AMIA), 2013 –
Society for Judgment & Decision Making (SJDM), 2016 – 2017

Honors & Awards

Delta Omega (Public Health Honors Society), 2020
Med About Data Hackathon (Haifa, Israel) – Second Place, 2019
Cerner Population Health Leadership Development Program, 2015
Cerner Masters Award, 2014