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The Adoption and Use of Health Information Technology in Three Settings

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The Adoption and Use of Health Information Technologies in Three Settings

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Doctor of Philosophy in Health Services

by

Jeffrey Carroll McCullough

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ABSTRACT OF THE DISSERTATION

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Jeffrey Carroll McCullough

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University of California, Los Angeles, 2013

Professor Hector Rodriguez, Chair

Health information technology (IT) has become an increasingly common part of the U.S. healthcare system. This three-paper dissertation examines barriers, facilitators, and correlates of health IT adoption and impacts of health IT use in several important settings.

The first paper examines the impact of electronic warnings in diverting non-indicated prescriptions in ambulatory settings. Specifically, we measured the incidence of antibiotic prescriptions for acute bronchitis and upper respiratory infections using a nationally-representative dataset. We found evidence that, overall, electronic warnings reduce the likelihood of antibiotic prescription receipt by about 20%. However, despite the recent increase in use of electronic warnings, antibiotic prescribing is not on the decline, suggesting that electronic warnings alone may not be sufficient to eliminate non-indicated prescriptions.

The second paper provides the first cross-year comparison of the use of electronic health records (EHRs) at local public health departments (LHDs) in the U.S. Using 2005

and 2010 data from the National Association of City and County Health Officials, we found that EHR usage has remained relatively steady at local public health departments. There is substantial churn, however, with approximately one-quarter of the sample adopting EHRs and another fifth of the sample discontinuing use of EHRs. Our study suggests that EHRs are not diffusing throughout LHDs as they are in other healthcare settings. Our results highlight departmental characteristics under which EHRs are commonly used and suggest potential places, such as poor or rural areas, where use of EHRs may be lower than expected.

The third paper examines participation in health information exchange (HIE) in two settings where HIEs have proven slow to diffuse—smaller-sized physician practices and federally qualified health centers (FQHCs). We conducted key informant interviews with stakeholders at practices and clinics. Our results suggest barriers to HIE adoption that exist at three levels—regional (e.g., existence of other area-level exchanges; number, type, and size of partner organizations), inter-organizational (e.g., strong relationships with exchange partners; achieving a critical mass of users), and intra-organizational (e.g., type of electronic medical record used; integration into organization's workflow). While some of these factors may be modifiable by health care organizations, limited solutions to overcome these barriers currently present a major challenge to the broad and effective use of HIE.

The dissertation of Jeffrey Carroll McCullough is approved.

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2013

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VITA

Jeffrey McCullough received a Master of Public Health with a concentration in Public Health Policy from the University of Minnesota and a Bachelor of Science in Foreign Service with a concentration in Science, Technology, and International Affairs from Georgetown University. He has worked as a Graduate Student Researcher at the University of California, Los Angeles Fielding School of Public Health from 2010 to 2013 and prior to that served as a Research Assistant at the University of Minnesota School of Public Health. He was Co-Chair of the Board at the Phillips Neighborhood Clinic in 2009-2010. He worked as a Program Associate at the National Academy of Sciences and as a Program Assistant at the U.S. Department of State. He has co-authored five refereed publications, two policy monographs, and fifteen peer-reviewed reports to the U.S. Congress.

McCullough is a recipient of the University of California, Los Angeles Dissertation Year Fellowship, the University of California, Los Angeles Graduate Research Mentorship, and the Agency for Healthcare Research and Quality Pre-Doctoral Traineeship. He received the Barbara Ann Walton Spradley Leadership Award and was a Walter H. Judd International Graduate Fellow at the University of Minnesota. He is a member of the Delta Omega Honorary Society.

Chapter I:

Introduction

The U.S. healthcare system is beset by problems of rising costs (Centers for Medicare and Medicaid Services 2011) and variable quality (Fisher, Wennberg et al. 2003; Institute of Medicine 2003). Health information technology (health IT) has been proposed as one potential solution to these problems (Orszag and Emanuel 2010). Partially as a result, it has seen a recent uptick in policy attention and a commensurate surge in investment (Blumenthal 2009).

Large and well-resourced hospitals have traditionally led the way in adoption of many types of health IT (Blumenthal 2009; Jha, DesRoches et al. 2009). Office-based ambulatory providers, smaller-sized clinics or practices, and other ancillary members of the U.S. health care system have been less likely to adopt (Burt and Sisk 2005; Shields, Shin et al. 2007; Jha, DesRoches et al. 2009). A common refrain is that health IT is simply too expensive, both in terms of initial expenses and ongoing maintenance costs, to justify its adoption.

Financial incentives have been promoted with the goal of spurring wider adoption and use of health IT. The Health Information Technology for Economic and Clinical Health (HITECH) Act under the 2009 American Reinvestment and Recovery Act aimed to spur "meaningful use" of health IT through incentive payments to hospitals and providers of up to $44,000 per clinician through Medicare and $63,750 per clinician through Medicaid over 10 years (Blumenthal 2009). In addition, penalties of 1% reduction in Medicare reimbursements will begin in 2015 and increase to 3% by 2018. The totality of these reimbursement changes roughly approximate the financial costs of adoption—estimated at approximately $35,000 per clinician per year for small- and medium-sized ambulatory providers (Miller, West et al. 2005; Fleming, Culler et al. 2011).

As we might expect, evidence suggests that health IT is becoming more common. As of 2002, less than 20% of office-based ambulatory providers had adopted electronic medical records while more than half had done so by 2011 (Burt and Sisk 2005; Hsiao, Hing et al. 2010). Comparisons across studies, however, may be problematic due to different target populations, different types of health IT examined, and evolving definitions of health IT over time (Burt and Sisk 2005; DesRoches, Campbell et al. 2008; Jha, DesRoches et al. 2009; Decker, Jamoom et al. 2012). Nevertheless, a preponderance of evidence suggests that health IT is being used in more places now than ever.

Much research and policy attention has been paid to measuring and tracking the use of specific types of health IT in specific settings, for example electronic medical records in hospitals (Jha, DesRoches et al. 2009) and ambulatory settings (DesRoches, Campbell et al. 2008). While it is undoubtedly important to have accurate estimates of the prevalence of various types of IT in our health care system, it is also important to have additional information on its overall effects. Thus it may become more important to focus attention towards additional areas beyond measuring and promoting meaningful use. This dissertation focuses on three such areas believed to be critical next-steps for health IT research in the U.S.

The first paper (Chapter II) centers around our ability to track, at a national level, the effects of health IT usage on important clinical quality indicators. It is estimated that health IT will have major impacts on both patient safety (Institute of Medicine 2012) and overall costs (Hillestad, Bigelow et al. 2005). In order to accurately assess safety gains and cost savings, we must have evidence not only from specific hospitals, specific systems, or specific states, but national estimates as well. To date, many studies have focused on the impact of changes in a single setting (Mainous, Lambourne et al. 2013), partially because it did not make sense to attempt to generate national estimates when usage levels were still low. Going forward this is anticipated to be a major data need for policy makers, practitioners, and researchers.

The second paper (Chapter III) focuses on the use of health IT by a vital component of the public health care system in the U.S.—city and county public health departments. While the use of health IT by hospitals and ambulatory providers has been carefully tracked for some time, the same attention has not been paid to local health departments despite their important contributions to the assurance of the public's health. Public health departments may play an important role in current and future electronic data exchanges as repositories of clinical and public health data. To this end, electronic health records (EHRs) at local health departments (LHDs) may be useful for intra-departmental work and for inter-organizational cooperative work performed with community partners. Relatively little is known about where EHRs are being used by LHDs and existing studies do not facilitate cross-year comparisons of EHR use in these settings. High levels of use may signal an important role for LHDs as repositories of information and critical components for successful data exchange efforts. Low levels of use may signal a need for additional consideration of how EHRs can be tailored to meet the needs of LHDs to ensure they also receive the benefits projected to stem from the use of health IT.

The third paper (Chapter IV) focuses on two specific settings which are underrepresented in terms of health IT usage, especially with respect to electronic data exchange such as health information exchanges (HIEs). These two settings, small physician practices and federally qualified health centers (FQHCs), play crucial roles in delivering care for the majority of Americans (Ross, Schilling et al. 2010), especially for uninsured or underinsured individuals. However, these settings lag relative to larger hospitals in HIE participation. With an eye towards eventually developing strategies to measure readiness for engagement with HIE among these groups, this chapter focuses on identifying specific facilitators and barriers to participation in current HIE efforts. This information might help promote the uptake of HIE in these settings, which may be important to patch the health IT and HIE participation holes in an otherwise rapidly-adopting U.S. healthcare system.

These papers collectively address three issues hypothesized to be crucial for better understanding where, how, and why health IT is being used. Improved forecasts of overall use will be important, but a deeper understanding of the interaction between individuals, organizations, and the IT systems themselves is essential (Sittig and Singh 2010).

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Chapter II:

Impact of e-Warning Capability on Receipt of Antibiotic Prescriptions for Acute Bronchitis and Upper Respiratory Infection

Abstract

Antibiotics are commonly accepted to be non-indicated for acute bronchitis and upper respiratory infection (URI), yet widespread use of both narrow- and broad-spectrum antibiotics persists. Electronic warnings are hypothesized to alert providers to divert non-indicated prescriptions. The purpose of this study was to identify the effect of electronic warnings on a highly visible type of non-indicated prescription.

Using five years' of data from the National Ambulatory Medical Care Survey (2006 – 2010), ambulatory visits with primary diagnoses of acute bronchitis or URI and orders for antibiotic prescriptions were identified. Visits were classified based on clinician reports of e-warning use. Generalized estimating equations were used to assess the effects of e-warnings on antibiotic prescribing and on likelihood of antibiotic prescription receipt, controlling for patient, provider, practice characteristics.

Findings suggest that clinician use of electronic warning increased sharply from 2006 (16%) to 2010 (55%) of visits. During this time period, use of e-warning was associated with a 19% lower likelihood of receiving an antibiotic prescription, controlling for several confounders (95% CI: 4% to 33% lower). The effect persisted in alternative models that included variables on year-specific adoption trends.

All the same, antibiotic prescribing for acute bronchitis and URI remained steady over time (35% – 45% of visits) because of a secular upward trend in antibiotic prescribing which offset the downward pressure from increased use of e-warning systems. Use of e-warning was not associated with a change in the likelihood of broad versus narrow spectrum antibiotic receipt.

The overall effect of electronic warnings suggests a potential role for technology in reducing non-indicated prescriptions. However, data suggest that electronic warnings alone

may not be sufficient to eliminate non-indicated prescriptions and that other secular trends may be at play.

Introduction

Health information technology (health IT) is often touted as a strategy for reining in healthcare spending while also improving quality of care (Institute of Medicine 2012). To this end, the Health Information Technology for Economic and Clinical Health (HITECH) Act was passed in 2009 to spur adoption and "meaningful use" of health IT. As part of the meaningful use requirements, healthcare organizations and providers are required to make use of clinical decision support systems, which can include electronic warning (e-warning) systems or "alerts" to highlight potential contraindications for prescriptions ordered.

Meaningful use of e-warnings could reduce medication errors, inappropriate, or unnecessary prescriptions. This effect has been demonstrated in some cases, such as the substitution of generic for branded medication (Stenner, Chen et al. 2010). Other studies have yielded mixed results when examining the impact of e-warning use on contraindicated prescriptions for elderly patients (Smith, Perrin et al. 2006) and the impact of adding an e-warning for medications with black-box warnings to an existing EMR (Yu, Seger et al. 2011). Their results indicated that EMR warnings had mixed effects on prescribing behavior, though both studies noted significant positive impacts of warnings for specific types of prescriptions or "clinically important subcategories." An overall, nationally-representative assessment of the impact of e-warning on contraindicated prescriptions has not been conducted.

A major challenge to advancing understanding of the impact of e-warnings on prescribing behavior are the multiple mechanisms in which e-warnings may work to alter the number or type of prescriptions ordered during a patient-clinician encounter. Depending on the circumstance, the optimal outcome may involve additional prescriptions, the substitution of one prescription for another, or the diversion of one or more prescriptions. To better understand the overall impact of e-warnings, it is necessary to narrow the focus to a specific set of encounters and resulting prescriptions over the broadest possible population. In particular, prescriptions which provide little to no benefit to individual patients or to the population at large are especially concerning as the overuse not only provides no additional value to the healthcare system, their systematic overuse may actually detract value. One such example is non-indicated antibiotic prescriptions. We examine the use of antibiotics prescribed for primary diagnoses of acute bronchitis or upper respiratory infection (URI).

Antibiotics & Acute Bronchitis/URI

Antibiotics generally provide little to no benefit for most cases of acute bronchitis and URI (Dowell, Marcy et al. 1998; Gonzales, Bartlett et al. 2001; Gonzales, Bartlett et al. 2001; Tan, Little et al. 2008). Non-indicated prescriptions of antibiotics are not only wasteful from an economic perspective, they are also of particular concern due to rising levels of antibiotic-resistant microorganisms (Spellberg, Guidos et al. 2008). Despite their ineffectiveness, prescriptions for antibiotics remain common in primary care (Mainous III, Hueston et al. 2003; Grijalva, Nuorti et al. 2009). Reflecting this concern, the American Academy of Pediatrics and the American College of Physicians have both issued guidelines for reducing antibiotic use for acute bronchitis and URI (Dowell, Marcy et al. 1998; Snow, Mottur-Pilson et al. 2001). The Healthcare Effectiveness Data and Information Set (HEDIS) measure has, since 2008, tracked antibiotic prescriptions for acute bronchitis through their NQF-endorsed "Avoidance of antibiotic treatment in adults with acute bronchitis" measure (National Quality Measures Clearinghouse 2013). This has made antibiotic prescriptions for acute bronchitis or URI one of the more visible quality measures and a prime candidate for widespread diversion. Additional distinctions have been made between broad- and narrow-spectrum antibiotics, with broad spectrum antibiotics of particular concern as they may disproportionately contribute to antibiotic resistance (Steinman, Landefeld et al. 2003).

In spite of these efforts to reduce use, antibiotic prescriptions for acute bronchitis and other respiratory tract infections persist (Grijalva, Nuorti et al. 2009; Evertsen, Baumgardner et al. 2010). Indeed, some estimate that up to 50% of all antibiotic prescriptions are for non-clinically-indicated viral respiratory infections (Nyquist, Gonzales et al. 1998; Cantrell, Young et al. 2002). Large-scale studies using national data reveal that, while overall levels of antibiotic prescribing may be on the decline, rates remain problematically high (Mainous III, Hueston et al. 2003; Grijalva, Nuorti et al. 2009).

In short, there is strong conceptual rationale that e-warnings may successfully divert non-indicated prescriptions in certain settings. Yet existing studies have typically employed customized technology and in other ways might not be generalizable to typical clinical practice (Smith, Perrin et al. 2006; Yu, Seger et al. 2011). This leaves unanswered the question of whether these promising clinical results for e-warnings can be translated from efficacy to effectiveness.

To date, the overall impact of e-warnings on the diversion of non-indicated prescriptions such as antibiotics for acute bronchitis or URI has not been assessed in a large, national sample. On the heels of some headline-garnering estimates of cost savings and productivity gains flowing from widespread adoption of health IT (Hillestad, Bigelow et al. 2005), it is important to generate system-level estimates of the actual impact of specific systems and whether we are realizing the anticipated benefits of health IT investments at the national level.

Objective

This study seeks to strengthen the existing literature on the impact of health IT on ambulatory care through examination of the impact of e-warning on antibiotic prescriptions for outpatient cases of acute bronchitis and URI. We use diffusion of innovation theory to guide our examination of the observed effects of e-warning using separate cross-sectional samples for each year from 2006 – 2010. As this study uses five years of data, we aim to examine trends in the adoption of health IT by office-based ambulatory providers from 2006 through 2010 and clarify the extent to which the relationship of e-warnings and antibiotic prescribing change over time.

Logic Model

The logic model for this study is shown in Figure 1 (figures shown at end of document). The primary relationship of interest is provider use of e-warning and receipt of antibiotic prescription for visits with primary diagnosis of acute bronchitis or URI.

In a basic explanatory framework of outpatient antibiotic overprescribing, Nyquest et al. suggest four possible causes: education, experience, expectations, and economics (Nyquist, Gonzales et al. 1998). We hypothesize that e-warnings act to improve condition-specific education and enhance a clinician's previous experiences (Paez, Roper et al. 2013). This should yield fewer non-indicated antibiotic prescriptions for acute bronchitis or URI, with ancillary benefits of improved clinical performance and patient safety.

To accurately assess the true relationship between use of e-warning and receipt of antibiotic prescription, several potential confounders are addressed through the study's logic model. The first set of variables hypothesized to be relevant to both e-warning use and prescribing patterns is a provider's use of other forms of health IT.

In this study, two empirical proxies will be used for health IT use: provider's use of e-prescribing and provider's use of EMR. Use of e-prescribing may influence provider behavior in a multitude of ways (Bell, Cretin et al. 2004), many of which would influence a provider's likelihood of prescribing an antibiotic for visit with diagnoses of acute bronchitis or URI (Overhage, Perkins et al. 2001). For example, a provider with a treatment style featuring a higher propensity to prescribe may not only be more likely to prescribe antibiotics, he or she may also be more likely to adopt the e-prescribing system to facilitate such frequent prescriptions. On the other hand, physicians who have a higher predisposition towards seeking out additional information through uncertainty reduction techniques such as diagnostics or extended patient interviews are likely to use EMR (Lanham, Sittig et al. 2013) and, perhaps as a result of this additional information available, may be able to make an improved treatment decision (Miller and Sim 2004), including fewer non-indicated antibiotic prescriptions. a given patient and may enable a clinician to make a better treatment decision.

Several other factors can impact provider responses to e-warnings. Provider practice setting factors such as office type (i.e., private practice, HMO, other) and physician specialty are related to both likelihood of e-warning and health IT usage and antibiotic prescribing practices (Mainous III, Hueston et al. 2003; Hsiao, Hing et al. 2010). For example, clinicians in a HMO setting are more likely to have access to an e-warning system (Jha, DesRoches et al. 2009) and may be differentially likely to order antibiotic prescriptions—perhaps due to shared risk arrangements, inclusion patient satisfaction factors or follow-up care received in consideration of clinician performance or compensation (Schwartz, Mainous III et al. 1998).

Patient factors such as type of insurance used (Nyquist, Gonzales et al. 1998; Coco and Mainous 2005) and patient race/ethnicity (McCaig and Hughes 1995) may also impact prescribing patterns through expectations and economic incentives. Adoption of e-warning and other health information technologies has been shown to vary across clinicians serving large proportion of privately insured versus Medicaid or other insurance types (Hing and Burt 2009; Butler, Harootunian et al. 2013) and patient race/ethnicity is associated with differing levels of access to technologies such as e-warning (Jha, DesRoches et al. 2009) and differing underlying expectations regarding antibiotic prescriptions (Nyquist, Gonzales et al. 1998). Additional factors including patient age and the presence of pulmonary-related chronic conditions such as asthma or chronic obstructive pulmonary disease (COPD) provide additional information about the conditions of the patient visit, as both age and underlying medical conditions are likely to impact a clinician decision making with respect to antibiotic prescriptions (Nyquist, Gonzales et al. 1998; Mainous III, Hueston et al. 2003).

Finally, we allowed for the possibility that practice specialty moderated the hypothesized relationship between e-warning use and antibiotic prescribing. General practitioners and specialists more likely to prescribe antibiotics than pediatricians and primary care physicians, (Nyquist, Gonzales et al. 1998), likely because they have less frequent experience with such cases. Clinicians with less experience with a specific diagnosis or treatment may be more apt to rely on or defer to the warnings provided relative to a clinician with more experience.

Methods

Data

Data from the 2006, 2007, 2008, 2009, and 2010 National Ambulatory Medical Care Surveys (NAMCS) were used for this study. NAMCS is a nationally representative survey of non-federally employed, office-based providers providing ambulatory medical care services (National Center for Health Statistics 2009). NAMCS sampling and data collection methods are described in detail elsewhere (National Center for Health Statistics 2009). Briefly, NAMCS data are collected from a nationally-representative, stratified sample of clinicians on an annual basis. Each clinician provides data on a random sample of patient visits during a one-week period. Information includes visit-level data for patient demographics and symptoms, diagnostics ordered, diagnoses, prescriptions ordered, and referrals provided. Additional clinician-level data include demographics and practice characteristics (National Center for Health Statistics 2009). Further information on the NAMCS is available in the supplementary material section at the end of this chapter.

Analytic Sample

The size of the annual dataset ranges from 28,871 (2008) to 32,771 (2007) ambulatory care visits, with over 1,000 providers sampled per year. Each provider has an average of approximately 25 patient visits included in the survey (ranging from a low of 1 to a maximum of 72). For this study, five years of NAMCS data were utilized. The NAMCS sample is refreshed annually and there is no method to link responding clinicians or patients across years. Data for each year were combined to create the analytic sample, with indicator variables for each study year.

Variables

Bronchitis & Upper Respiratory Infections

We used International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9) diagnosis codes from the NAMCS dataset to identify a total of 3,810 visits with a primary diagnosis of bronchitis or URI (Acute bronchitis, ICD-9 code 466, n=511; Bronchitis not otherwise specified, ICD-9 code 490, n=758; Acute URI of multiple or unspecified sites, ICD-9 code 465, n = 2,416; Acute nasopharyngitis, ICD-9 code 460, n = 125). The study's inclusion criteria are consistent with other studies on antibiotic prescribing patterns for acute bronchitis and URI (Nyquist, Gonzales et al. 1998; Mainous III, Hueston et al. 2003; Coco and Mainous 2005; Mainous, Lambourne et al. 2013).

Cases where at least one of the patient's secondary diagnoses would indicate an antibiotic prescription were excluded (n=493). Exclusion criteria are consistent with previously published studies of antibiotics prescribing for non-indicated cases (Mainous III, Hueston et al. 2003; Coco and Mainous 2005; Mainous, Lambourne et al. 2013). Exclusionary secondary diagnoses, their corresponding ICD-9 codes, and the number of cases excluded by each are shown in detail in the supplementary material section at the end of this chapter (see Table S2). The final analytic sample was 3,317 acute bronchitis or URI visits over the 5 years.

Antibiotic Prescriptions

A full list of antibiotic medications was obtained from the National Committee for Quality Assurance (NCQA) Healthcare Effectiveness Data and Information Set (HEDIS)

"Avoidance of Antibiotic Treatment for Adults with Acute Bronchitis" list (NCQA, 2013). The full list is shown in the appendix (Table S3). Codes for each of these prescriptions were then manually matched to the NAMCS dataset using the NAMCS drug entry list and generic codes data. The vast majority of prescriptions contained exact matches in the NAMCS codebook. Of the 78 prescriptions listed, nine relatively uncommon entities (italicized in Table S3) were not located in the NAMCS codebook and are not included in this analysis. A board-certified internal medicine physician reviewed this coding strategy for accuracy and completeness.

Use of E-Warnings

The primary independent variable is the provider's use of an e-warning system during the patient-provider encounter. Use of e-warning was assessed in the NAMCS provider survey with the question: "Are there warnings of drug interactions or contraindications provided?" Response categories included: Yes, No, Unknown, Turned Off. Respondents were considered as having the technology if they answered, "Yes". While very uncommon (n=50 to 150 per year), Unknown and Turned Off were not considered as having access to e-warnings for the purposes of this study.

Covariates

Multivariable models controlled for several factors outlined above in the logic model. Provider's use of e-prescribing and provider's use of EMR were assessed at the clinician level by NAMCS and were added as dichotomous variables. A categorical description of the clinician's office type was included with three categories: private practice, HMO, and other. Clinician specialty was also included as a three category variable—general practitioner, pediatrics, and all others. Patient factor variables included insurance type (private, Medicare, Medicaid, self-pay, and other), age (0-4, 5-17, 18-64, 65+), race/ethnicity (non-Hispanic white, non-Hispanic black, Hispanic, other), and dichotomous variables for the presence of two pulmonary-related chronic conditions—asthma and COPD.

Additional information is available in the supporting material section at the end of this chapter (see Description of Covariate Coding section).

Statistical Analyses

To track trends in antibiotic prescribing over time, univariate statistics were compiled for each year for antibiotic prescriptions ordered, e-warning, health IT usage variables, and all other model covariates. Bivariate statistics for antibiotic use for non-indicated cases and all covariates were also calculated.

Survey weights were used to present descriptive and bivariate statistics in order to account for the NAMCS sampling design and generate national-representative estimates. The use of survey weights would be required only if there is reason to suspect effect-modification by NAMCS sampling variables—such as geography or practice specialty (DuMouchel and Duncan 1983), survey weights were nevertheless employed as they facilitate cross-year comparisons within the sample and comparisons of study findings with previous studies which also make use of survey weights (Nyquist, Gonzales et al. 1998; Mainous III, Hueston et al. 2003; Coco and Mainous 2005; Mainous, Lambourne et al. 2013).

Multivariable generalized estimating equations (GEE) with an exchangeable correlation structure (Liang and Zeger 1986) were specified to estimate the overall effect of e-warning on receipt of antibiotics, controlling for the potential confounders discussed in the logic model above. The GEE-exchangeable models used the binomial family and logit link function.

We then ran the models for each year separately to assess changes over time (2006 – 2010) in the relation of e-warnings and antibiotic prescribing behavior as e-warning use is increasing over time. Finally, to estimate the effect of e-warning on receipt of broad versus narrow spectrum antibiotics, a separate GEE model predicting was specified to those acute bronchitis or URI visits in which any antibiotic was prescribed.

Postestimation tests were performed for all regression models to calculate marginal probabilities and risk ratios. Risk ratios were bootstrapped with 1,000 repetitions using the percentile method to avoid imposing the distributional assumptions of the normal approximation method.

Additional analyses were performed to test the sensitivity of results to variable coding and model specifications. The study's coding of e-warning and other forms of health IT is consistent with some (Romano and Stafford 2011) but not all (McCormick, Bor et al. 2012) previous studies using this dataset. This study's measure construction was selected as the default for this study because meaningful use standards eventually call for all providers to actually use these technologies, not merely to just install them and turn off their functionalities. Sensitivity analyses revealed that overall results were not sensitive to this measure construction.

All coding and analysis was performed using Stata version 13.1

Results

The study's analytic sample is summarized below in Table 1; averages for the entire analytic sample and a year-by-year breakdown are both shown. Of particular note in Table 1are the meaningful, and statistically significant, increases in the proportion of providers using e-warning, e-prescribing, and EMR between 2006 and 2010.

Figure 2 (see end of chapter) shows antibiotic prescription orders for outpatient visits with primary diagnosis of acute bronchitis of URI. For the entire sample, 39.8% of acute bronchitis/URI visits resulted in antibiotic prescriptions. In each year, approximately upwards of 70% of all antibiotic prescriptions were for broad spectrum antibiotics. There appears to be an upward trend across the years, though this is not statistically significant at the $\alpha = .05$ level.

Table 1: Characteristics of Ambulatory Care visits for acute bronchitis/URI, by year

Variable		**2006**	**2007**	**2008**	**2009**	**2010**	**All years**
Patient received antibiotic prescription		34.1	40.3	40.6	38.8	45.4	39.8
Provider uses e-warning		16.1	17.6	34.6	39.9	54.5	31.8
Provider uses e-prescribing		13.2	16.2	30.4	35.9	55.6	29.4
Provider uses EMR		14.5	18.7	25.1	36.2	47.3	27.9
Patient Insurance Type	Private	56.0	54.2	61.2	52.9	55.8	55.8
	Medicare	7.6	13.6	13.6	14.1	12.8	12.4
	Medicaid	25.5	21.0	17.9	27.2	23.6	23.2
	Self-pay	2.6	4.7	3.4	3.1	2.4	3.3
	Other	2.0	1.9	0.9	1.1	3.0	1.7
Provider Office Type	Private practice	85.4	87.9	89.4	90.1	86.3	87.9
	HMO	2.0	1.8	1.3	1.2	2.8	1.8
	Other	12.6	10.3	9.3	8.3	10.9	10.3
Provider specialty	Pediatrics	35.3	38.2	36.1	32.8	36.3	35.7
	General/family medicine	42.4	36.6	41.5	47.4	37.1	41.1
	Other	22.3	25.2	22.5	19.8	26.7	23.2
Patient age	0 – 4	29.3	29.2	30.5	22.9	30.5	28.3
	5 – 17	19.0	20.6	16.5	22.3	18.7	19.5
	18 – 64	42.1	35.4	37.8	39.9	37.6	38.6
	> 65	9.6	14.8	15.3	14.9	13.2	13.6
Patient race	Non-Hispanic White	62.6	63.4	67.4	69.0	66.1	65.6
	Non-Hispanic Black	12.2	10.7	9.8	10.6	12.2	11.1
	Hispanic	17.1	14.6	13.7	15.6	15.5	15.3
	Other	8.0	11.4	9.1	4.9	6.3	8.0
Patient chronic condition(s)	None	3.8	3.2	4.2	6.5	4.1	4.4
	Asthma	7.8	8.9	9.4	8.4	10.9	9.0
	COPD	*28.7*	*24.7*	*23.3*	*26.9*	*19.9*	*24.9*

Bivariate analyses were also conducted, but were not used in the model building process as they may not indicate the true nature of the relationship between use of e-warning and antibiotic prescribing for acute bronchitis or URI. These comparison tables are shown in the supplementary material section at the end of this chapter (see Table S4 & Table S5).

A multivariate GEE model regressing receipt of antibiotic prescription in cases of acute bronchitis or URI on provider's use of e-warning and other relevant covariates revealed that use of e-warnings are significantly reduced odds of antibiotic prescription receipt. A full set of model estimates is shown in Table 2. After adjusting for other covariates in the model, the odds of a provider ordering an antibiotic prescription for acute bronchitis or URI visits are 0.63 times as great for providers who have e-warning systems than for providers who do not have such systems (p < .05).

Table 2: Odds Ratios from GEE Regression on Receipt of Antibiotic Prescription

Variable		**Odds Ratio**
Provider uses e-warning		0.62 *
Provider uses e-prescribing		1.37
Provider uses EMR		1.21
Provider specialty:	Pediatrics	*Reference*
	General/family medicine	1.93 **
	Other	1.45
Provider Office Type:	Private practice	*Reference*
	HMO	0.21 ***
	Other	1.00
Patient Insurance Type:	Private	*Reference*
	Medicare	0.91
	Medicaid	0.69 **
	Self-pay	1.09
	Other	0.82
Patient age:	0 – 4	0.63 **
	5 – 17	0.75
	18 – 64	*Reference*
	> 65	0.69
Patient race:	Non-Hispanic White	*Reference*
	Non-Hispanic Black	1.34
	Hispanic	0.85
	Other	0.46 **
Patient chronic condition(s):	Asthma	0.99
	COPD	2.97 ***
NAMCS Survey Year:	2006	*Reference*
	2007	1.46 *
	2008	1.44 *
	2009	1.20
	2010	1.88 ***

* p < .05
** p < .01
*** p < .001

Relative risks were calculated for e-warning for the overall sample (all years) and separately for each year using GEE models stratified by NAMCS survey year. As shown in table 5, in each year of the sample e-warnings were not significantly associated with a change in the likelihood of antibiotic prescription receipt. The magnitude of the point estimate of the effect remains somewhat similar across years, though the wide 95% confidence intervals preclude discussion of the significance of these findings. This may be due to the modest sample sizes present for each year (median n = 631).

It has been hypothesized that early-adopters may be more sympathetic to the goals of e-warning systems, and that accordingly the effects of e-warnings would be greater in earlier years and less in later years as the technology is more widely adopted. Table 3 does not show any evidence of such a pattern. The differences across years are not significant, which may reflect small sample size, but the point estimates do not reflect any decay in effectiveness over time.

Table 3: Relative risk of receipt of antibiotic prescription with use of e-warning, by year

Year(s)	N	Relative risk of receiving antibiotic prescription with clinician use e-warning (95% confidence interval+)
All years	3,317	0.81 (0.66 , 0.96)
2006	694	0.83 (0.35 , 1.53)
2007	722	0.98 (0.68 , 1.46)
2008	631	0.93 (0.63 , 1.37)
2009	690	0.85 (0.59 , 1.22)
2010	580	0.81 (0.59 , 1.14)

+ Confidence intervals bootstrapped using 1,000 repetitions, percentile method shown.

A model that included an interaction term for the use of e-warning and the overall proportion of providers using e-warning in a given year revealed results highly consistent with those presented in table 2. The coefficient for the interaction term was not significant while the odds ratio and standard error for the e-warning coefficient were largely unchanged.

Next, to examine the impact of e-warning on broad versus narrow spectrum antibiotic prescribing practices, we limited the sample to acute bronchitis/URI visits for which an antibiotic prescription was ordered (n=1259). Using the same GEE model as described above, we found that clinician's use of e-warning had no effect on the likelihood of broad- versus narrow-spectrum antibiotic receipt. Full model results are shown in the supplementary material section in Table S6.

We calculated the overall regression-adjusted probability of receiving an antibiotic prescription during a visit for acute bronchitis or URI, shown in Figure 3. The trend suggests that, at any given point in time, e-warning helps reduce the likelihood of antibiotic prescriptions for acute bronchitis or URI. But there is an upward secular trend for both groups. On net, as the composition or e-warning users changes, antibiotic rates remain the same, even though e-warning helps and is expanding.

Finally, to provide some context for the estimate of the effect of e-warning on antibiotic prescribing, the NAMCS data used in this study represent an average of approximately 830 million ambulatory encounters per year between 2006 and 2010. Of these, approximately 11 million visits were for acute bronchitis or URI. With approximately 40% of all such visits resulting in an order for an antibiotic prescription, around 4.4 million such prescriptions occur annually. A 20% decline in the proportion of visits for acute bronchitis or URI could thus mean at least 440,000 fewer potentially harmful or wasteful antibiotic prescriptions per year (assuming approximately half of clinicians use e-warning, as in 2010) or potentially as many as 880,000 fewer prescriptions annually if all clinicians were to use e-warnings.

Discussion

Our study, the first large-scale, nationally-representative examination of the association of electronic warning with orders for antibiotic prescriptions in cases of acute bronchitis or URI found that despite ongoing efforts aimed at reducing or eliminating prescriptions for such diagnoses, a substantial proportion—nearly 40%—of outpatient visits with acute bronchitis or URI result in a prescription for antibiotics.

These results present a mixed picture. On the one hand, there is evidence that e-warnings were effective in reducing non-indicated antibiotic prescribing. At the same time, e-warning systems were becoming more widely adopted from 2006 to 2010. Yet an upward secular trend in antibiotic prescribing has wiped out gains that may otherwise have accrued with wider use of e-warnings. More research will be required to understand the reasons for this upward secular trend.

The level of prescribing did not vary significantly between 2006 and 2010. In addition, we found that despite public awareness campaigns and guidelines, use of broad spectrum antibiotics appeared to be at least as prevalent, if not more, than previously estimated (Steinman, Landefeld et al. 2003), with no apparent downward trend.

Consistent with the existing literature, NAMCS data from 2006 to 2010 reveal a sharp increase in clinician use of three forms of health IT: e-warning, e-prescribing, and EMR. Each rose from approximately 10 – 15% prevalence in 2006 to over 50% by 2010. We believe this diffusion and the resulting diverse range of users is a strength of this study as it enabled us to measure the effect of e-warning on the "early adopters" using in 2006 and the "early/late majority" using in 2010 (Rogers 2003).

With respect to the impact of e-warning on antibiotic prescriptions for acute bronchitis and URI, results of our results suggest that, after accounting for relevant patient and provider factors, the use of e-warning systems is associated with a significantly lower likelihood of receiving an antibiotic prescription. Specifically, the likelihood of receiving an antibiotic prescription is 0.82 times as great for acute bronchitis or URI visits where the provider reports having e-warning capabilities as for visits where the provider reports not having them. Other forms of health IT, including electronic medical records and e-prescribing, did not have any significant impact on the likelihood of receiving an antibiotic prescription for non-indicated cases. All of the categorical patient- and clinician-level covariates included in our model were significant. We interpreted this as evidence that the net effectiveness of e-warnings, as with many other forms of health IT, depends on a matrix of patient- and clinician-level sociotechnical factors (Sittig and Singh 2010).

Our estimate of the impact of e-warnings on prescribing is consistent with previous studies examining the impact of a specific clinical decision support system or technological intervention on prescribing behavior for acute bronchitis/URI (Belongia, Knobloch et al. 2005; Ranji, Steinman et al. 2008) and for other evidence-based prescription diversion efforts (Christakis, Zimmerman et al. 2001). The "modest" effect size of e-warning we found is roughly comparable to other studies of individual CDS systems (Mainous, Lambourne et al. 2013) or of CDS plus community interventions (Samore, Bateman et al. 2005) on antibiotic prescribing patterns.

This study expands upon this earlier research by providing an estimate of the overall impact of e-warning systems nationwide for patients with bronchitis. This estimate suggests a 20% decline in the likelihood of antibiotic prescription associated with e-warning, which could represent hundreds of thousands of averted prescriptions that are wasteful and in some cases harmful.

In an effort to add context to this estimate, we also calculated the relative risk associated with use of e-warning and receipt of antibiotic prescription for each year in the sample (2006 through 2010, inclusive). Some past studies have used a slightly wider inclusion criteria to increase sample size—including cases of common cold, for example (Mainous III, Hueston et al. 2003)—though we did not due to the possible lack of electronic warnings for less clear-cut non-indications. Even though the point estimate for most of the years was substantively similar to the overall estimate, the wide confidence intervals preclude any findings of significance.

We also ran a model that included an interaction term between use of e-warning and overall proportion of providers using e-warning in the year in which the visit took place. If we believe that the observed e-warning effect is not due to the warnings themselves but to some underlying construct, say attentiveness-to-quality, that is associated with both the likelihood of e-warning usage and the likelihood of antibiotic prescribing. As e-warning became much more common between 2006 (16% of visits) and 2010 (55% of visits), we are thus able to observe in this dataset those most attentive-to-quality (the early adopters in 2006) and those who are slightly less attuned-to-quality (in the early and later majority in 2010). In this scenario we would expect the observed relationship to attenuate over time. This model demonstrated that this did not occur for acute bronchitis visits between 2006 and 2010, as the effect of e-warning was significant and similar in magnitude with and without these year-specific and interaction term alternative model specifications.

Together these results suggest that there is no greater effect of e-warning systems among early adopters than among later adopters. This should strengthen confidence in the conclusion that the e-warning itself that is responsible for the observed effects and not an unmeasured covariate or merely spurious correlation.

With respect to the types of antibiotic prescriptions ordered, we found no effect of e-warning on broad versus narrow spectrum antibiotics. While we might have expected warnings to be especially beneficial in averting broad spectrum prescriptions as these are hypothesized to be especially problematic at the system-level, there was no effect due to e-warnings. It is possible that the specific warnings currently being generated by clinicians' systems do not adequately differentiate between broad and narrow spectrum agents.

Strengths & Limitations

Our study has several limitations to note. First, our measure of e-warning usage was limited in the NAMCS dataset. Namely, the systems are measured at the provider level rather than at the visit level. Previous studies have shown that there is variation in IT functionality usage at the organization (Wang, Marken et al. 2005) and clinician levels (Crosson, Isaacson et al. 2008; Pevnick, Asch et al. 2010). In addition the NAMCS dataset does not contain information on the specific conditions or warnings generated by each clinician's system. Some of the providers who report using e-warning may not have used the system or been exposed to the specific alerts or warnings that would help in averting antibiotic prescriptions for acute bronchitis or URI. Thus, we cannot be sure that all of the reported e-warning users were subject to the effect of the warnings for antibiotic prescriptions. Reassuringly, however, this type of cross-classification measurement error would tend to dilute the effect and impart a bias towards the null. In essence this is akin to an efficiency study rather than an efficacy study. This conservative bias may have thus understated the true impact of the warnings themselves.

Second, our study was beset by similar problems to most large-scale studies of health IT systems. Namely, we were not able to measure the contextual (Paez, Roper et al. 2013) or sociotechnical (Yusof, Kuljis et al. 2008; Sittig and Singh 2010) factors that are often hypothesized to moderate the impact of health IT on patient safety. Hypothesized by some to be a moderator of IT system effectiveness, these contextual factors are notably absent from all large scale datasets (Paez, Roper et al. 2013) so this limitation is not unique to our study.

Third, although we utilized multiple years' of cross-sectional data and carefully accounted for other factors hypothesized as relevant to the study's conceptual model, we are not able to prove causation. It could be argued that e-warning users and non-users are different groups. Of course, this difference would only be problematic insofar as it is both unmeasured in this study and results in differential antibiotic prescribing practices for acute bronchitis or URI visits. To mitigate this potential source of uncertainty, we have presented statistical and conceptual rationale in the discussion above for why spuriousness is not likely the cause of our findings. We also note that use of e-warnings has diffused rapidly throughout our study period. Whatever between-group differences that may have existed in 2006 would have been at least partially diluted by later adopters who used e-warnings by 2010 (Rogers 2003).

Fourth, our study may have been limited by somewhat small samples for each year of data, limiting the sub-sample analyses possible. Nevertheless, the NAMCS dataset is the largest and most broadly representative dataset available for this study, with rich visit-specific and provider-specific data. By pooling several years of data we were able to overcome this potential limitation, though we were thus unable to identify any trends over time in the impact of e-warning on antibiotic prescribing practices for acute bronchitis or URI.

Finally, with any un-randomized trial, it is difficult to ascribe causality to the relationships observed. We performed several additional analyses to extend findings to

Conclusion

Taken together, our results suggest an ambiguous impact of e-warning in reducing antibiotic prescribing for acute bronchitis and URI. On the whole, there does appear to be a roughly 20% decrease in the likelihood of antibiotic prescription receipt. In addition to the effect of e-warning itself, several patient- and clinician-level variables also helped explain antibiotic prescribing practices among the study's nationwide ambulatory care sample. This reiterates the complex and interdependent nature of prescriptions and emphasizes the role that technology can play in achieving desired outcomes in conjunction with efforts aimed at other system stakeholders.

An effect of this size might be expected to avert nearly a half-million non-indicated antibiotic prescriptions annually, a major achievement and one that could help clinicians improve the care they deliver and their performance on at least one HEDIS measure.

However, when we analyzed subsamples or subgroups these effects became statistically insignificant. One potentially fruitful area for additional attention is distinction between broad versus narrow spectrum antibiotics. If broad spectrum agents are an area of particular concern that we wish to target for further reduction, further attention to the frequency, type, and severity of warnings generated for broad versus narrow spectrum prescriptions may be a fruitful area for additional attention for clinician groups, IT systems leadership, and policy makers to address.

Whatever the case, however, the magnitude of the reduction in likelihood of antibiotic prescription receipt for acute bronchitis or URI due to use of e-warnings does not suggest that this strategy alone will result in the elimination of this practice.

Figures

Figure 1: Logic Model for Study

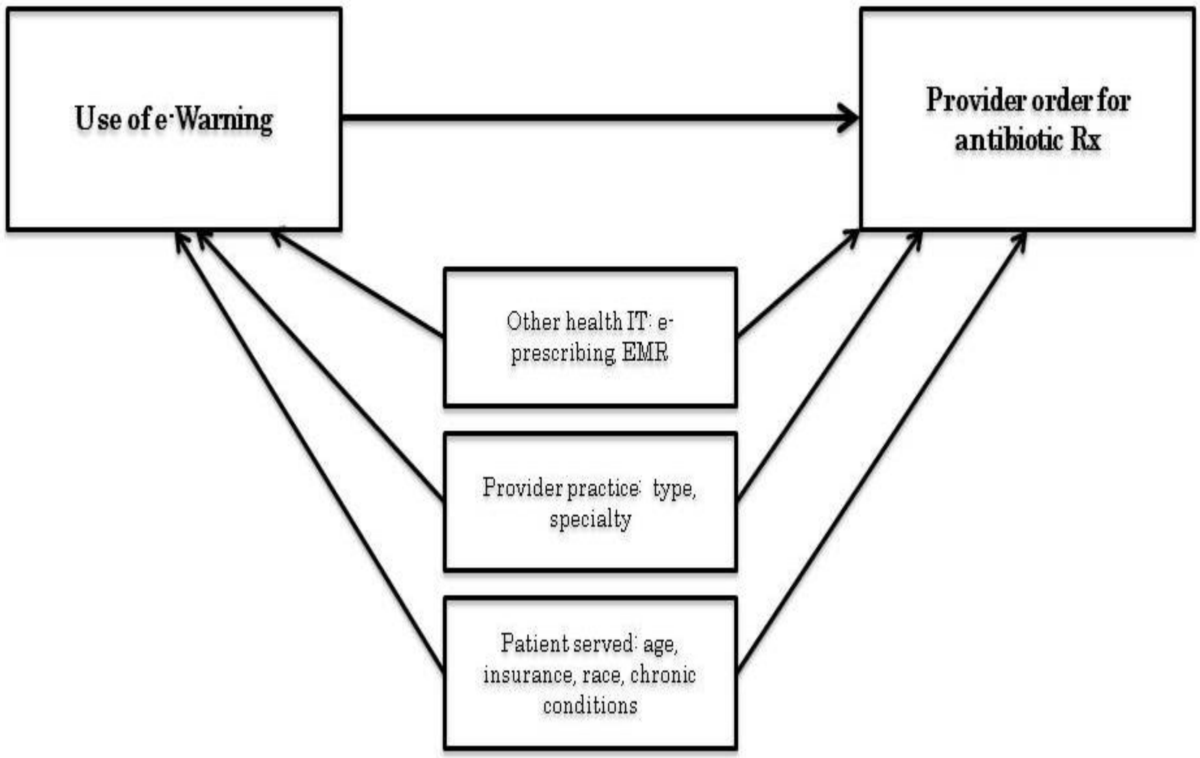
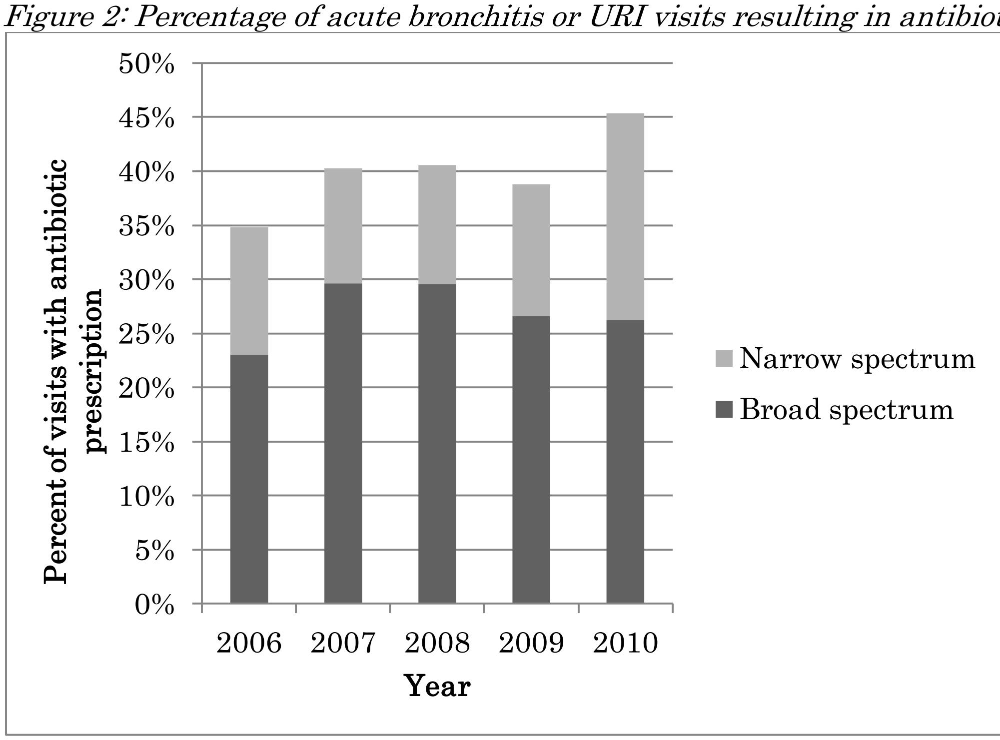
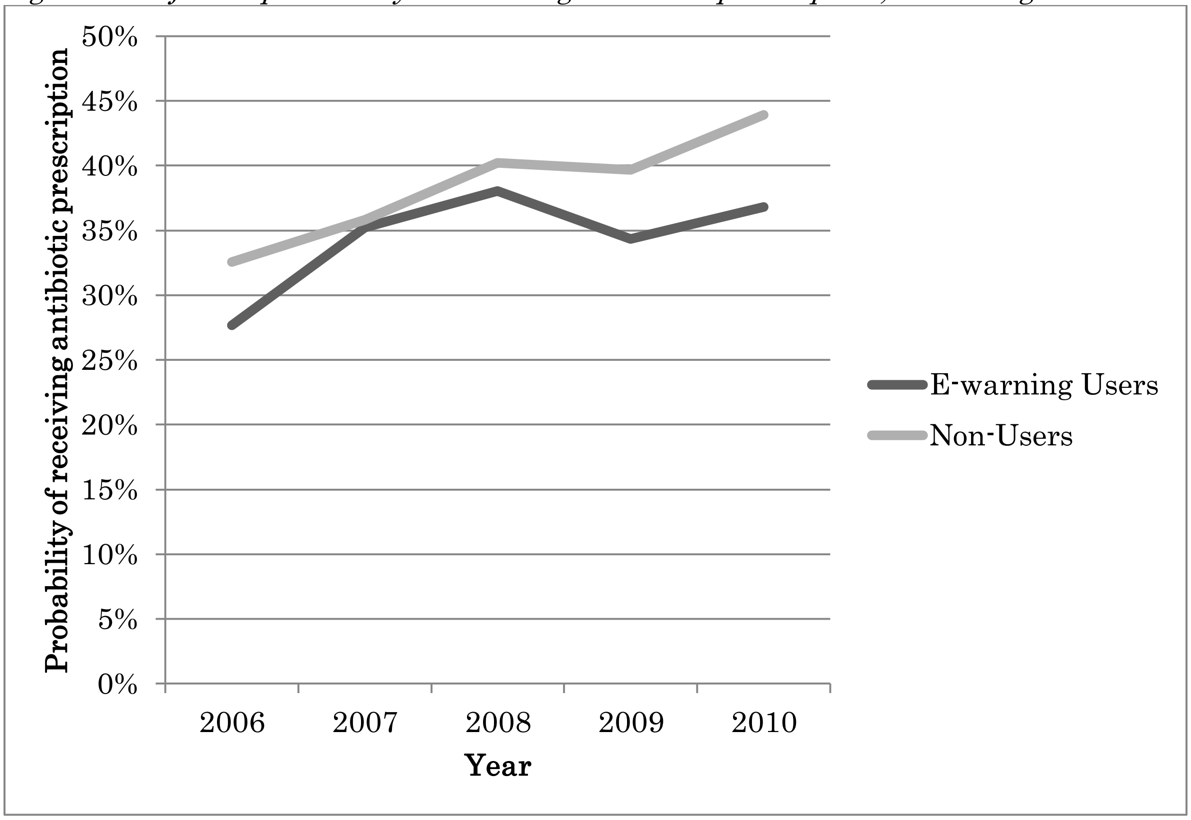


Figure 2: Percentage of acute bronchitis or URI visits resulting in antibiotic prescription



Note: No between-year differences significant at p = .05

Figure 3: Adjusted probability of receiving antibiotic prescription, e-warning versus non



Supplementary Material

Table S1: Conceptual Model Specification

Theoretical Variable	Empirical Proxy	Hypothesized direction of effect	Rationale
Receipt of antibiotic prescription for acute bronchitis or URI	Prescription for antibiotic ordered, as reported to NAMCS (Y/N)	*(Dependent Variable)*	*(Dependent Variable)*
Provider's use of e-warning during visit	Provider medical group self-reported overall use of e-warning (Y/N)	↓	Rationale described in text.
Other health IT systems in use	Provider medical group self-reported overall use of e-prescribing (Y/N)	↑	e-prescribing may make prescribing easier than paper-based systems.
	Provider medical group self-reported overall use of EMR (Y/N)	↓	Additional information to better tailor treatment and/or additional IT capabilities stemming from EMR use may limit prescriptions
Provider practice setting	Provider's specialty: • Pediatrician • General & family practice • All other	 *Reference* ↑ ↔	Pediatricians see more cases of bronchitis and URI than others and are less likely to prescribe than general practitioners. Other specialties may or may not see cases frequently so the direction of the relationship is unknown.
	Provider's practice type: • Private practice • HMO • Other	 *Reference* ↓ ↔	Relative to the private practice reference group, HMOs should have fewer new prescriptions due to the clinician's organization being at risk for the associated costs. Other settings (Mental health centers, Faculty practices, Community health centers, Government clinics, Family planning, Freestanding, FQHC) may have differing incentives for IT adoption & prescriptions

			so directionality is unclear.
Patient served	Patient's (primary) type of insurance used during visit: • Private • Medicare • Medicaid • Self-pay • Other	*Reference* ↔ ↓ ↓ ↔	Relative to the private insurance reference group, Medicare patients may be roughly similar due to roughly comparable payments and provider Medicaid may see fewer antibiotics due to limited reimbursements and provider resources. Self-pay visits may be the same or less due to price sensitive patients. No specific directional effect is hypothesized for the "Other" category.
	Patient's age: • 0 – 5 years • 5 – 18 • 18 – 64 • 65+	↑ ↑ *Reference* ↔	Children are more likely to receive antibiotics than adults because of parental requests and may be more likely to be seen in non-IT rich settings. It is unknown how the elderly compare to the adults. Variable was categorized to accommodate hypothesized non-linearities with relationship of interest.
	Patient's race/ethnicity: • Non-Hispanic White • Non-Hispanic Black • Hispanic • Non-Hispanic Other	*Reference* ↔ ↔ ↔	This proxy will help assess the ease of patient-provider communication. An ideal proxy would include information on language concordance but this is the best proxy available. Reference group will be Non-Hispanic White. It is unknown how each race/ethnicity will compare to the others.
	Patient has pulmonary-related chronic condition(s) as reported to NAMCS (Asthma, cerebrovascular disease, COPD).	↑	Presence of a chronic condition may increase the complexity of the visit and therefore the likelihood of a prescription. These visits may also be more likely to be conducted in IT-rich settings.

National Ambulatory Medical Care Survey (NAMCS) Overview

As briefly outlined in the main portion of this chapter, the NAMCS is a nationally-representative dataset aimed at collecting objective, reliable information about the provision and use of ambulatory medical care services in the United States. The data are collected exclusively from the clinician, rather than the patient as in other surveys such as the National Health Interview Survey (NHIS) or the Medical Expenditure Panel Survey (MEPS), to “provide an analytic base that expands information on ambulatory care collected through other NCHS surveys” (National Center for Health Statistics 2009).

NAMCS includes data on patients’ health status and symptoms, clinician diagnoses, diagnostic services ordered during visit, medications ordered, and demographic characteristics of patients and services provided, including information on diagnostic procedures, patient management, and planned future treatment.

The population of interest is all visits occurring at non-federal and non-hospital-affiliated ambulatory care settings. The NAMCS is a repeated cross-section survey. The sample is refreshed annually and there is no method of linking respondents or patients across survey waves. The sampling methodology includes probability samples of primary sampling units (PSUs), physician practices within PSUs, and patient visits within practices.

The first-stage sample includes 112 PSUs. The second stage consists of a probability sample of practicing physicians selected from the master files maintained by the American Medical Association and the American Osteopathic Association. Within each PSU, all eligible physicians were stratified by 15 practice specialty types. The final stage is the selection of patient visits within the annual practices of sample physicians involving two steps. First, the total physician sample is divided into 52 random subsamples of approximately equal size, and each subsample is randomly assigned to 1 of the 52 weeks in the survey year. Second, a systematic random sample of visits is selected by the physician during the reporting week. The sampling rate varies for this final step from a 100 percent sample for very small practices, to a 20 percent sample for very large practices as determined in a presurvey interview. Data on a mean of approximately 25 patient visits for each clinician are included in the NAMCS (range: 1 – 75).

Table S2a: List of All Antibiotics Used to Construct Study's Dependent Variable

Description	**Prescription**		
Aminoglycosides	amikacin gentamicin	kanamycin *streptomycin*	tobramycin
Aminopenicillins	amoxicillin	ampicillin	
Antipseudomonal penicillins	piperacillin	*ticarcillin*	
Beta-lactamase inhibitors	amoxicillin-clavulanate ampicillin-sulbactam	piperacillin-tazobactam	ticarcillin-clavulanate
First-generation cephalosporins	cefadroxil	cefazolin	cephalexin
Fourth-generation cephalosporins	cefepime		
Ketolides	*telithromycin*		
Lincomycin derivatives	clindamycin	lincomycin	
Macrolides	azithromycin clarithromycin	erythromycin erythromycin ethylsuccinate	*erythromycin lactobionate* *erythromycin stearate*
Miscellaneous antibiotics	aztreonam chloramphenicol dalfopristin-quinupristin	daptomycin erythromycin-sulfisoxazole linezolid	metronidazole vancomycin
Natural penicillins	penicillin G benzathine-procaine penicillin G potassium	*penicillin G procaine* *penicillin G sodium*	penicillin V potassium penicillin G benzathine
Penicillinase resistant penicillins	dicloxacillin	nafcillin	oxacillin
Quinolones	ciprofloxacin gatifloxacin *gemifloxacin*	levofloxacin lomefloxacin moxifloxacin	norfloxacin ofloxacin sparfloxacin
Rifamycin derivatives	rifampin		
Second generation cephalosporin	cefaclor cefotetan	cefoxitin cefprozil	cefuroxime *loracarbef*
Sulfonamides	sulfadiazine sulfamethoxazole-trimethoprim	sulfisoxazole	
Tetracyclines	doxycycline	minocycline	tetracycline
Third generation cephalosporins	cefdinir cefditoren cefixime	cefotaxime cefpodoxime ceftazidime	ceftibuten ceftriaxone
Urinary anti-infectives	fosfomycin nitrofurantoin nitrofurantoin macrocrystals	nitrofurantoin macrocrystals-monohydrate trimethoprim	

Table S2b: Subset of Antibiotics Defined as "Broad Spectrum" for analyses

Description	Prescription		
Beta-lactamase inhibitors	amoxicillin-clavulanate		
Macrolides	azithromycin clarithromycin		
Quinolones	ciprofloxacin	levofloxacin	norfloxacin
	gatifloxacin	lomefloxacin	ofloxacin
	gemifloxacin	moxifloxacin	sparfloxacin
Second generation	cefaclor	cefoxitin	cefuroxime
cephalosporin	cefotetan	cefprozil	*loracarbef*
Third generation	cefdinir	cefotaxime	ceftibuten
cephalosporins	cefditoren	cefpodoxime	ceftriaxone
	cefixime	ceftazidime	

Table S3: Exclusion Criteria for Secondary Diagnoses Indicating Antibiotic Prescription

Diagnosis Description	*ICD-9 Codes*	*Number Excluded*
Nonsuppurative otitis media	381	0
	381.01	3
	381.1	0
	381.2	0
	381.3	0
	381.4	0
Suppurative otitis media	382	149
Acute sinusitis	461	31
Chronic sinusitis	473	119
Acute pharyngitis	462	132
Acute tonsillitis	463	12
Streptococcal sore throat	034.0	7
Pneumonia	481	0
	482	1
	483	0
	484	0
	485	0
	486	15
Bacterial infections	041	5
Urinary tract infections	590	0
	595	0
	597	0
	599.0	7
Acne	706.1	4
Emphysema among adults	492	3
Chronic bronchitis among adults	491	3

Description of Covariate Coding

EMR use was assessed on the NAMCS with the item: "Does this practice use electronic MEDICAL RECORDS (not including billing records)?" Response categories included: Yes, all electronic; Yes, part paper and part electronic; No; Don't know. Respondents were considered to be using electronic medical records if they answered "Yes, all electronic".

E-prescribing use was assessed on the NAMCS questionnaire with the item: "Are prescriptions sent electronically to the pharmacy?" Possible response categories included Yes, No, Unknown, Turned Off. As with e-warnings, respondents were only considered as having the technology if they answered Yes. Usage of both e-prescribing and the study's primary predictor of interest, e-warning, was only asked of clinicians who indicated having a computerized system for orders for prescriptions.

The National Center for Health Statistics cleans and imputes data for many of the variables (National Center for Health Statistics 2010), so of the 3,317 total visits included in the sample, the only variable with any missing data was patient's urban/rural location, with 39 missing values. Since urban location was by far the more frequent in NAMCS, these observations were logically imputed to urban. Sensitivity analyses that excluded these 39 observations revealed that findings were not sensitive to this coding decision.

For one variable, changes in NAMCS questionnaire design between 2006 and 2010 resulted in re-coding of response categories. Patient race/ethnicity, a seven-category variable in 2006 – 2008, was changed to a four category variable for 2009 and 2010. This four category version was used for all years.

Finally, to ensure model stability, variables were re-coded to eliminate categories with very few or no observations. For example, for patient insurance type, "used worker's compensation" and "no charge/charity" were combined into an existing "other" category. Likewise, provider's practice type had several categories with extremely small counts (freestanding clinics, federally-qualified health centers, non-federal government clinics, family planning clinics, and faculty practice plans) that were combined into an 'other' category as they were not specifically hypothesized to be associated with the primary relationship of interest.

Bivariate Analyses

Table S4 below bivariate comparisons between the receipt of antibiotic prescription and the main predictor of interest—use of e-warnings—and the study's other covariates. These bivariate comparisons suggest that use of e-warning is not significantly associated with receipt of antibiotic prescription. Likewise, e-prescribing and EMR are not significantly associated with receipt of antibiotic prescription in cases of acute bronchitis or URI.

Table S5 below a bivariate comparison between the primary predictor of interest (provider use of e-warning) and the study's other covariates. Comparisons are shown for the entire sample (all years) and for the study's first (2006) and last (2010) years of data.

Table S4: Proportion of bronchitis/URI visits with Antibiotic prescription

Variable		Received Antibiotic Prescription (%)
Overall		39.8
e-warning	User	40.7
	Non-User	37.9
e-prescribing	User	39.7
	Non-User	40.1
EMR	User	39.7
	Non-User	39.8
Patient Insurance Type	Private **	42.5
	Medicare *	47.1
	Medicaid ***	27.8
	Self-pay *	53.9
	Other	40.8
Provider Office Type	Private practice	40.1
	HMO ***	12.3
	Other	42.4
Provider specialty	Pediatrics ***	25.7
	General/family med ***	49.4
	Other	44.6
Patient age	0 – 4 ***	25.8
	5 – 17 *	33.6
	18 – 64 ***	51.4
	> 65	45.2
Patient race	Non-Hispanic White **	43.3
	Non-Hispanic Black	44.5
	Hispanic *	31.1
	Other ***	21.3
Patient chronic condition(s)	None	29.8
	Asthma	40.4
	Chronic Obstructive Pulmonary Disease ***	61.7
NAMCS Survey Year	2006	34.8
	2007	40.3
	2008	40.6
	2009	38.8
	2010	45.4

* $p < .05$
** $p < .01$
*** $p < .001$

Table S5: Bivariate comparison of Use of e-Warning versus other study covariates

Variable		Entire Sample Use of e-warning: Doesn't Use (68.2%)	Entire Sample Use of e-warning: Uses (35.1%)	2006 Only Use of e-warning: Doesn't Use (83.9%)	2006 Only Use of e-warning: Uses (16.1%)	2010 Only Use of e-warning: Doesn't Use (45.5%)	2010 Only Use of e-warning: Uses (54.6%)
Provider uses e-prescribing		10.6%	89.4% ***	11.6%	88.4% ***	10.5%	89.5% ***
Provider uses EMR		24.4%	75.6% ***	19.9%	80.1% ***	14.4%	85.6% ***
Patient Insurance Type:	Private	65.9%	34.1% *	81.0%	19.1%	40.7%	59.3%
	Medicare	64.9%	35.1%	84.7%	15.3%	47.0%	53.0%
	Medicaid	74.4%	25.6%	91.1%	8.9% *	55.0%	45.0%
	Self-pay	79.6%	20.4%	92.1%	8.0%	59.2%	40.8%
	Other	79.1%	20.9%	86.0%	14.0%	69.8%	30.2%
Provider Office Type:	Private practice	69.2%	30.8%	85.0%	15.0%	47.0%	53.0%
	HMO	32.6%	67.4% **	29.9%	70.1% ***	46.3%	53.7%
	Other	66.0%	34.0%	85.3%	14.7%	33.0%	67.0%
Provider specialty:	Pediatrics	69.7%	30.3%	85.7%	14.3%	42.8%	57.2%
	General/family medicine	69.5%	30.5%	80.6%	19.4%	49.4%	50.7%
	Other	63.8%	36.2%	87.2%	12.8%	43.6%	56.4%
Patient age:	0 – 4	68.4%	31.6%	80.7%	19.3%	48.3%	51.7%
	5 – 17	70.5%	29.5%	86.1%	13.9%	40.2%	59.8%
	18 – 64	68.6%	31.4%	86.5%	13.5%	44.5%	55.5%
	> 65	63.5%	36.5%	77.8%	22.2%	49.0%	51.0%
Patient race:	Non-Hispanic White	66.1%	33.9% *	84.1%	16.0%	41.7%	58.4%
	Non-Hispanic Black	74.9%	25.1%	90.7%	9.3%	53.2%	46.8%
	Hispanic	70.7%	29.3%	81.6%	18.4%	52.1%	47.9%
	Other	71.2%	28.2%	77.2%	22.8%	53.9%	46.1%
Patient chronic condition(s):	Arthritis	72.0%	28.0%	39.6%	10.4%	57.9%	42.1%
	Asthma	64.2%	35.8%	80.6%	19.4%	37.8%	62.2%
	COPD	73.9%	26.1% *	90.6%	9.4% *	45.7%	54.3%

* p < .05
** p < .01
*** p < .001

Table S6: Odds Ratios from GEE model for receipt of Broad Spectrum Antibiotic Prescription for visits resulting in any antibiotic prescription

Variable		**Odds Ratio**
Provider uses e-warning		1.04
Provider uses e-prescribing		1.13
Provider uses EMR		0.79
Provider specialty:	Pediatrics	*Reference*
	General/family medicine	1.10
	Other	1.44
Provider Office Type:	Private practice	*Reference*
	HMO	0.51
	Other	0.67
Patient Insurance Type:	Private	*Reference*
	Medicare	0.82
	Medicaid	1.46
	Self-pay	2.20 *
	Other	1.73
Patient age:	0 – 4	1.25
	5 – 17	0.63
	18 – 64	*Reference*
	> 65	2.10 **
Patient race:	Non-Hispanic White	*Reference*
	Non-Hispanic Black	0.44 ***
	Hispanic	0.61 *
	Other	0.98
Patient chronic condition(s):	Asthma	1.18
	COPD	1.25
NAMCS Survey Year:	2006	*Reference*
	2007	1.32
	2008	1.41
	2009	1.14
	2010	1.19

* p < .05
** p < .01
*** p < .001

Table S6: Odds Ratios from GEE model for receipt of antibiotic prescription, with e-warning/yearly interaction term

Variable		Odds Ratio
Provider uses e-warning		1.04
Interaction Term: E-warning*Proportion of providers using e-warning in survey year		2.30
Provider uses e-prescribing		1.40*
Provider uses EMR		1.03
Provider specialty:	Pediatrics	*Reference*
	General/family medicine	2.03***
	Other	1.93***
Provider Office Type:	Private practice	*Reference*
	HMO	0.24**
	Other	0.89
Patient Insurance Type:	Private	*Reference*
	Medicare	0.96
	Medicaid	0.79*
	Self-pay	1.29
	Other	0.80
Patient age:	0 – 4	0.63**
	5 – 17	0.85
	18 – 64	*Reference*
	> 65	0.78
Patient race:	Non-Hispanic White	*Reference*
	Non-Hispanic Black	1.23
	Hispanic	0.81
	Other	0.54***
Patient chronic condition(s):	Asthma	0.87
	COPD	2.71***

* p < .05
** p < .01
*** p < .001

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Chapter III:

Local Public Health Department Adoption & Abandonment of Electronic Health Records

Abstract

While local health departments (LHDs) play a crucial role in assessing, assuring, and monitoring the public's health, little is known about their current utilization of technologies such as electronic health records (EHRs) that may facilitate the ability of LHD involvement in an increasingly digitized healthcare system. The results presented here provide the first assessment of EHR use that is directly comparable across years and use diffusion-of-innovation and institutionalism theories to test sets of predictors associated with EHR adoption and use. Combining data from the nationwide National Association of City and County Health Officials profile report on LHDs and the Area Resource File, we performed logistic and multinomial logistic regression models to assess EHR use in 2010 and adoption, use, or abandonment of EHR between 2005 and 2010.

We found that EHR use declined slightly between 2005 and 2010, with approximately 28% of LHDs reporting usage in 2005 and 21% by 2010. In addition to this, the make-up of users and non-users changed, with both adoption and abandonment of EHR common in our sample of 401 LHDs in 2005 and 514 LHDs in 2010. Resource-based predictors including clinical service measures and per-capita expenditures were much stronger predictors of LHD EHR use than were institutional predictors such as leadership or governance characteristics. LHDs serving poorer and rural areas were also less likely to report EHR use.

Our study suggests that EHRs are not diffusing throughout LHDs as they are in other healthcare settings. Our results highlight departmental characteristics under which LHDs are commonly used and suggest potential places, such as poor or rural areas, where adoption and use of EHR may be slower than expected.

Introduction

Local health departments (LHDs) are the primary vehicle through which the public's health is assessed, assured, and monitored (Institute of Medicine 2002). These activities are undertaken by LHDs in partnership with community organizations, with funding (Mays and Smith 2009), structure (Mays, Scutchfield et al. 2010), and performance (Mays, Halverson et al. 1998; Freund and Liu 2000; Mays, McHugh et al. 2004; Erwin 2008) that vary widely between local public health jurisdictions. The services provided by LHDs require a capacity to receive, interpret, and produce information on the health of their service-area population. The electronic information systems and technology to help track and manage this data are broadly defined as public health informatics. One of the major forms of public health informatics that is highly relevant to both LHDs and to payment incentives under the HITECH Act is electronic health records (EHRs). An EHR contains health information of an individual and (unlike most electronic medical records) is capable of being shared across multiple organizations (Wager, Lee et al. 2009).

Reflecting the importance of EHRs to the national health IT and public health informatics landscape, the National Association of County & City Health Officials (NACCHO) Profile of Local Health Departments has collected data on LHD use of EHRs since 2005 and NACCHO devoted a chapter of its 2010 report "The Status of Local Health Department Informatics" to EHRs. Recently, the Public Health Accreditation Board (PHAB) updated its LHD accreditation standards to include guidance that accredited departments must document consideration of electronic health records among other emerging issues that may impact access to care (Public Health Accreditation Board 2013).

Thus there may be at least two broad sets of factors that could motivate LHDs to adopt and use EHR—those related to financial incentives or services delivered, referred to here as “resource-based”, and those related to normative pressures or experiences at peer departments, referred to here as “institutional”.

Whatever the underlying rationale for adoption, some LHDs are adopting EHRs. NACCHO data suggest that, as of 2010, more than half of LHDs providing primary or dental care services used some form of EHR (National Association of County and City Health Officials 2010), a substantial increase from the only 29% of all LHDs had implemented an EHR (National Association of County and City Health Officials 2006). Methodological differences between the two studies may have overstated this difference, however (see supplemental literature review section in supplemental material section at end of chapter). No studies have directly compared LHD EHR adoption estimates across multiple years. Without direct comparisons of LHD’s use of EHR usage over time, it is difficult to make informed decisions about whether and how to develop strategies to encourage the adoption and use of EHR by LHDs.

Research Aims

This study applies organizational behavior frameworks to identify potential predictors of EHR adoption and use between 2005 and 2010. The study had two primary research aims:

1. To examine use of EHR by local health departments in 2010, as predicted by LHD organizational and service-area characteristics in 2005.
2. To examine EHR adoption or abandonment between 2005 and 2010 (i.e., 2005 EHR use status versus 2010 use status) as predicted by two sets of factors:
    a. baseline organizational and service-area characteristics measured in 2005
    b. change in organizational and service-area characteristics from 2005 to 2010

Conceptual Framework

Reflecting the complex landscape of LHDs, the potentially heterogeneous influences that may affect adoption decisions for different forms of health IT, and the scarcity of previously published literature, multiple organizational theories are considered.

Diffusion of Innovation: Resource-Based Adoption Theory

Diffusion of innovation is a theory of how innovations spread—or fail to spread—between organizations (Rogers 2003). Under this theory, organizations might be hypothesized to conduct regular assessments of how an innovation could strengthen or extend their service capabilities and at what cost. Based on this rational calculus, a roughly predictable proportion of organizations would adopt a given innovation over time (Rogers 2003; Scott and Davis 2007).

Diffusion-of-innovation theory holds that earlier adopters can be differentiated from later adopters. Often they are driven more by resource-based predictors than later adopters (Rogers 2003; Scott and Davis 2007). These organizations tend to make adoption decisions based on an evaluation of how an innovation might strengthen or extend service capabilities and at what cost. Under this resource-based framework, LHDs might choose to adopt an EHR because they provide clinical services that may benefit from EHR or because the cost of maintaining a cache of paper clinical and surveillance records at a large LHD is greater than the cost of adopting and maintaining an EHR.

Under this framework, earlier adopters would be differentiable from later adopters based on these resource-based predictors (Rogers 2003; Greenhalgh, Robert et al. 2004). During later stages of the diffusion process, the differences between early and late adopters may become attenuated, perhaps due to the shrinking size of the pool of non-adopters or perhaps due to the role of a separate set of factors (Ferlie, Fitzgerald et al. 2005).

Mimetic Isomorphism: Institutional Adoption Theory

A separate set of factors hypothesized to underlie organizational decision-making are those that arise from outside of the organization. These forces might include professional norms arising from shared thinking or experiences, coercive forces such as regulatory or other legal responsibilities, or mimetic tendencies where one organization imitates practices or initiatives in other organizations. These are broadly defined as "institutional" factors that rise give to organizational isomorphism (Scott and Davis 2007), so called because . Under institutional theory, LHDs might choose to adopt an EHR in conjunction with their pursuit of public health accreditation (Public Health Accreditation Board 2013), because of positive experiences at a neighboring LHD, or because of governance pressures. Likewise, an LHD with leadership that is interconnected by professional ties with partners or other LHDs across the field might be persuaded by experiences at other adopting LHDs in making adoption decisions.

Institutional forces necessarily take time to permeate an industry as it depends upon the cumulative weight of experiences observed in other organizations, regulatory changes, and professional norms and expectations. As opposed to the focus on early adopters by diffusion of innovation theories, institutional theories focus on the processes that take place after innovations (such as the use of EHR in LHDs) are legitimized in the environment. Ultimately innovations reach a level of legitimization where failure to adopt is seen as less optimal, and sometimes even irrational or negligent if they become legal mandates, than adopting. Other organizations will therefore adopt the innovation even if it does not necessarily improve operations according to resource-based predictors.

Competing Theories & Conceptual Model

The resource-based and institutional theories are therefore well positioned to offer some insight as to where on the diffusion curve LHDs are with their use of EHR. If resource-based factors have stronger association with EHR use, we can be more confident that LHDs are still relying on an assessment of the value of an EHR more focused on factors internal to the organization. It may also mean that EHRs have not yet begun to diffuse widely throughout LHDs and that there is potential for more growth that might be promoted through policies and interventions targeted towards altering the EHR cost benefit calculus within LHDs. If institutional factors have stronger association with EHR use, we would be confident that EHR use has achieved some legitimacy among LHDs and that policies or interventions to further increase the perceived legitimacy of EHR use in LHDs would be preferable.

Since relatively little is known about the forces at play in EHR adoption decisions for LHDs, we focused on both sets of predictors of EHR adoption over time. With two competing explanatory frameworks, we aim to evaluate the importance of one relative to the other and to organize our findings according to the specific theories incorporated into our analyses and statistical models.

A conceptual model for the study's first research question was developed to examine LHD EHR use at a single point in time. The conceptual model is shown in Figure 1. Since there may be a lag in the effect of resource-based and isomorphic pressures on organizational decision-making, and due to the simple fact that EHR adoption can take time, it may take some time for these influences to impact LHD EHR use. Therefore, this study analyzed LHD predictors at an earlier point in time (2005) and EHR usage at a later point in time (2010). An additional benefit of using the lagged model approach is that potential reverse causality can be partially mitigated.

We extend the conceptual model to predict adoption, retention, and abandonment of EHRs by LHDs between baseline (2005) and follow-up (2010). We posit that changes in the organization's rational or institutional characteristics (between 2005 and 2010) impact LHD decisions to adopt or abandon EHRs. A regression-based approach enables us to assess the relative contribution of resource-based versus institutional factors in predicting EHR adoption and abandonment.

Methods

The target population for this study was all LHDs in the United States, a total of 2,565 as of 2010.[a] This target population is accessible through a comprehensive profile database on LHDs maintained by the National Association of County & City Health Officials (NACCHO).

First published in 1989, the NACCHO National Profile of Local Health Departments is now in its sixth iteration and is the nation's premier source of comprehensive data on the structure, function, and capacities of LHDs (Leep and Shah 2012). The 2005 Profile was the first to include information about the use of health IT by LHDs (National Association of County and City Health Officials 2006). The 2008 and 2010 Profiles also included survey questions about health IT use but many of the specific questions, wording, and answer choices changed slightly from the 2005 report (National Association of County and City Health Officials 2009; National Association of County and City Health Officials 2011). To allow for a sufficiently long period between measurements, and thus allow for the greatest amount of potential EHR adoption or abandonment, data from 2005 and 2010 (most recent

[a] Hawaii and Rhode Island are excluded from the study population because these states have no sub-state units (i.e., local health departments). Instead, their state health departments perform local public health functions. This arrangement would have differing organizational and operational structures and, as such, results from this study do not apply to these states.

available) were used in this study. The only common HIT question between the 2005 and 2010 waves was a question about LHD EHR adoption.

The methodology for the Profile report survey is described in detail in elsewhere (National Association of County and City Health Officials 2006; National Association of County and City Health Officials 2009; National Association of County and City Health Officials 2011). Briefly, every health department is sampled for each Profile wave. All LHDs receive a core questionnaire and, in addition, LHDs are randomly assigned to receive one of two (2010) or three (2005) modules. The overall response rates are quite high—80% in 2005 and 82% in 2010 (National Association of County and City Health Officials 2006; National Association of County and City Health Officials 2011). The high response rate coupled with the expansive target population means that this study will be reflective of and generalizable to the majority of LHDs in the U.S. The Profile data have been used in a variety of other peer-reviewed studies as a source of data about LHDs (Barnes and Curtis 2009; Wholey, Gregg et al. 2009; Beitsch, Leep et al. 2010; Parker, Shelton et al. 2012; Vest, Menachemi et al. 2012).

Measures

EHR: Consistent with previously published studies, health IT utilization was measured at the organizational level (Makoul, Curry et al. 2001; Jha, Ferris et al. 2006; Linder, Ma et al. 2007; Hsiao, Hing et al. 2010) using NACCHO Profile data from 2005 and 2010. Questions pertaining to the use of health IT are contained in a module, meaning that only a sub-sample of LHDs answer these questions in a given year. The LHDs that receive the health IT-relevant module are randomly sampled and change from year to year. In 2005, a total of 401 LHDs responded to the module containing questions on health IT use (81% response rate). In 2010, a total of 531 LHDs responded to the module containing questions on health IT use (85% response rate). There were 106 LHDs that responded to the health IT module in both 2005 and 2010.

One main advantage of our EHR measure is that it is present in multiple years' of Profile data. Limitations of this measure include a small change in the response options between years, the self-reported nature of the measure and the possibility that a 2010 respondent's interpretation of what constitutes an EHR and or what constitutes investigation or implementation of EHR adoption may differ from a 2005 respondent's.

Adoption

The study's main outcome of interest is whether an LHD reports using EHRs in a given year. As shown below in Table 1, we classified an LHD as a User if it reported that it had already implemented EHR. Sensitivity analysis, shown in the supplementary material section, showed that overall findings did not change when alternative definitions of EHR use were employed (e.g., counting LHDs as EHR users if they report that they 'have implemented' or that they are planning to do so).

This classification scheme was used because data came from a non-validated, self-administered questionnaire. To mitigate the potential for misclassification due to socially-desirable response bias (Bourque and Fielder 2003), all analyses were performed using only dichotomized versions of EHR usage. We defined EHR use as those LHDs who have fully implemented the technology, and not those that report that they are or will be implementing, have made the affirmative decision to adopt it.

Table 3: Response Categories for 2005 and 2010 NACCHO Profile Report Question on Electronic Health Record Usage at all LHDs

2005 (N=401)				2010 (N=514)			
Users	Implemented	112	27.9%	Have implemented	107	20.8%	Users
Non-Users	Planning to implement	39	9.7%	Planning to implement	89	17.3%	Non-Users
	Investigating or have investigated	105	26.2%	Investigating or have investigated	141	27.4%	
	Aware	122	30.4%	No activity in this area	120	23.4%	
	Not aware	23	5.7%	Not applicable	57	11.1%	

We examined EHR use at the organizational level. The extent of use within an organization is not measured and it is possible that within-organization diffusion varies widely. Measuring intra-organizational EHR diffusion is beyond the scope of the analyses.

Organizational Predictors of EHR Use

We also examine LHD organizational characteristics associated with EHR adoption and abandonment between 2005 and 2010.

Baseline data were obtained about LHDs from the 2005 NACCHO Profile and 2005 ARF dataset and at 'follow-up' from the 2010 NACCHO Profile and 2010 ARF dataset (or the closest ARF years available for a given measure). Table 2 below summarizes these variables. See supplementary material and Tables A1 & A2 for full descriptions of each.

Table 4: Independent variables used in study analyses

	Research Question 1: Predicting Use of EHR in 2010 2005 values used (except where noted)	Research Question 2: Predicting EHR Adoption from 2005 to 2010 Change in values from 2005 to 2010 used
Resource-based factors	Size of population served (standardized to mean = 0, standard deviation = 1)	% change in size of population served
	Proportion of LHDs serving: Urban Suburban Rural	
	Per capita expenditures (log)	% change in per capita expenditures
	LHD clinical services profile: Number of clinical services offered	LHD clinical services profile: Change in number of clinical services offered
	Number of clinical services contracted to other entities *Three clinical service measures were created through factor analysis (described below)*	Change in number of clinical services contracted
	LHD service area profile: *One summary area level factor created through factor analysis*	LHD service area profile: Percentage point change in FQHCs per capita Percentage point change in percent Medicaid eligible Percentage point change in percent unemployment
Institutional factors	Executive director has clinical background	New executive director
	LHD executive director is full-time position	
	LHD is governed by local board of health	Change in LBOH governance
	State-level governance	
	LHD controls IT hardware purchasing decisions (measured in 2005 only)	
	Plans to seek accreditation within 18 months (measured in 2010 only)	

Because model parsimony was a major priority with the modest LHD sample size, we conducted exploratory factor analyses to identify subgroups of variables for LHD clinical services provision and service-area characteristics and created subscales. Since a count of

LHD services offered may not fully measure the impact of providing a specific service or group of services, we conducted factor analyses to classify the clinical services[b] offered by the LHDs in 2005. Since the clinical service questions use dichotomous responses, exploratory factor analysis with a varimax rotation was conducted on the polychoric correlation matrix of the data (Pett, Lackey et al. 2003). As shown in Table 3, three factors were retained, all of which had Eigenvalues greater than 1.5. Three additional factors with Eigenvalue greater than one were not retained due to having only one service each with substantively meaningful loadings. Services whose loadings had an absolute value of less than 0.7 were not included when calculating factor scores.

Table 5: LHD clinical service offerings factors retained for analysis

Factor	Eigen value	Clinical Service (Loading*)	Descriptive Name
1	15.43	STD treatment (0.91), STD screening (0.90), HIV screening (0.90), HIV treatment (0.87), Family planning (0.80), Tuberculosis treatment (0.74), Tuberculosis screening (0.70)	Communic-able diseases
2	2.37	Diabetes screening (0.88), Cardiovascular disease screening (0.83), High blood pressure screening (0.82)	Chronic condition screening
3	1.60	Prenatal care (0.85), Obstetrical services (0.82)	Prenatal & Obstetrics

**Loadings with absolute value less than 0.7 were not used*

For the four area level measures, a separate factor analysis was performed using the three continuous measures available. Factor analysis was conducted with a varimax rotation (Kolenikov and Angeles 2009). A single factor was retained (Eigenvalue 1.16), referred to here as the area's poverty index, that loaded much higher onto percent Medicaid eligibles (0.70) and percent unemployment (0.68) than onto the per-capita number of

[b] The NACCHO dataset has information on 75 public health services. While there is no universally accepted methodology for measuring or counting public health service provision, one recent study pared the list of 75 services down to 29 clinical services (See Hsuan and Rodriguez, 2013). This study used this same set of 29 relevant clinical services to proxy for EHR-relevant public health service provision. Services that are not clinically oriented (e.g., air quality monitoring, animal control, etc.) are not relevant and are thus not included in analyses.

FQHCs (.20). Scales for the three clinical-service variables were obtained by averaging the scores for the items with loadings greater than 0.7 (Pett, Lackey et al. 2003). For the area poverty index, percent Medicaid eligibles and percent unemployment were both standardized to mean of zero standard deviation of one and and then averaged.

Analytic Sample

LHD Data

Health department data for this study came from three datasets, all provided by NACCHO. The three datasets were matched at the LHD level according to a department-specific ID that is assigned by NACCHO and used for all data collection activities.

The first datasets used were NACCHO Profile surveys from 2005 and 2010. These datasets provide the vast majority of information about LHDs for this study.

Second, in order to match LHDs to their geographic service area, Federal Information Processing Standard (FIPS) codes identifying the service area for each LHDs were obtained from NACCHO (National Association of County and City Health Officials 2013). Codes are available from 2008 and 2010 only. The 2010 version was used in this study to correspond with the follow-up measurements.

Third, since the study uses multiple years of LHD measurements and LHD jurisdictional changes have been occurring over time, e.g., consolidation of local health departments, data on LHD jurisdictional changes were obtained from NACCHO. A single variable was created for this study to indicate a jurisdictional change between 2005 and 2010.[c] None of the 106 LHDs for which baseline and follow-up EHR usage data were

[c] Jurisdictional change was also a major consideration in selecting the 2010 version of the FIPS codes as described above. Use of the 2008 version plus a variable indicating change between 2005 and

available were indicated as having undergone jurisdictional changes from 2005 to 2010. Of the 514 LHDs analyzed for the first research question, only 2 underwent any type of jurisdictional change (both were absorbed into other departments). These LHDs were excluded from analyses.

Area-Level Data

Area level data for LHD service area characteristics came from the ARF. The majority (85%) of LHD service areas are defined by a single FIPS code.

For LHDs that serve more than one county or have more than one FIPS code associated with them, ARF data for continuous variables were population-averaged for the entire service area. This methodology is consistent with previous studies (Grembowski, Bekemeier et al. 2010). Primary care health professional shortage area (HPSA) was measured as an indicator variable for each geospatial ARF unit. Once LHD service areas were reconciled with ARF units, an indicator variable was constructed to indicate whether any part of the LHD service area was a primary care HPSA.

2010 may not have fully identified service area and jurisdictional changes among LHDs in the sample.

Analysis

Research Question 1): To examine LHD EHR use in 2010 as predicted by resource-based and institutional factors measured in 2005, we focused on LHDs with data on EHR usage status for 2010 (n = 514). As described above, the outcome variable for this portion of the analysis was a dichotomous variable indicating use or non-use of EHR by each LHD in 2010.

Univariate statistics were computed to assess variation and distributions within the dependent, independent, and control variables. Bivariate analyses were performed to examine relationships with the dependent variable and assess correlation among control variables. Next, a lagged logistic regression model was run to examine whether hypothesized rational and institutional organizational characteristics from 2005 were associated with EHR usage in 2010. Risk ratios were calculated for variables which were borderline significant ($p<0.10$). Boostrapped confidence intervals were calculated using the percentile method and 1,000 repetitions (Wooldridge 2009).

Research Question 2): To examine EHR adoption or abandonment between 2005 and 2010, we focused on LHDs with EHR usage data for both 2005 and 2010 (N = 106).

LHDs were classified as users or non-users in 2005 and users or non-users in 2010. There are thus four possible categories of EHR usage between years (non-use, adoption, use, abandonment). Univariate and bivariate statistics with chi-square and ANOVA tests were used to examine significant associations and patterns.

Given the need for model parsimony for the adoption and abandonment analyses, both conceptual (proxies via conceptual model) and empirical (variation, reliability) considerations informed our selection of the final multinomial regression model.

The final multinomial regression model contained six variables: percent change in LHD per capita expenditures, difference in number of clinical services provided, change in each of the three LHD clinical service factors, and whether LHD had new executive director between waves. A Hausman test showed that the multinomial logistic model's independence of irrelevant alternatives assumption (IIA) was met. Small-Hsiao test of the IIA assumption was sensitive to the starting seed value. One possible explanation for this is the Small-Hsiao's use of subsamples, which may result in imprecise estimates in a sample of our size. Since the Hausman test does not subsample the data, the IIA assumption held and the multinomial logistic model was considered valid for these data. (Small and Hsiao 1985; Fry and Harris 1998; Long and Freese 2006; Cheng and Long 2007)

The likelihood ratio for combining alternatives suggested that all four outcome categories (non-use, adoption, use, and abandonment) were distinct from at least one other category, so the four-category outcome variable was retained for both conceptual and statistical reasons.

Given the difficulty in interpreting the coefficients from multinomial logistic models, predicted probabilities were obtained for each variable and are shown in plotted figures as described below.

Missing Data

Some covariates had missing values for some observations. Since the study sought to retain the maximum number of observations, complete case analysis was not feasible. Instead, several techniques were employed to logically impute missing values. These imputation methods and rationale are described in detail in supplementary material.

Additional Analyses

The study also considered several other analyses and models, including survey weights, longitudinal modeling, and other alternative model specifications. A host of sensitivity analyses were also performed to examine the sensitivity of findings to coding decisions and model specifications. These are described in supplementary material.

All analyses were performed using Stata version 13.1. Exemption from Institutional Review Board review (IRB#12-001501) was granted by the UCLA IRB due to the fact that no data on human subjects was used.

Results

EHR usage data were available for 2005 for 401 LHDs and for 2010 for 514 LHDs. Descriptive univariate statistics for the 2005 and 2010 samples are shown below in Table 4. The comparisons revealed a comparable sample between the two study waves. There were relatively small differences in most LHD characteristics. Changes in service-area characteristics reflect macroeconomic trends between 2005 and 2010.

Table 6: Characteristics of LHDs in sample (2005 & 2010)

LHD or Area-Level Characteristic		**2005**	**2010**
Resource-based factors	Mean size of population served	130,999	133,607
	Proportion of LHDs serving:		
	Urban	40.3%	40.7%
	Suburban	19.9%	19.9%
	Rural	39.8%	39.5%
	Mean per capita expenditures	$31.21	$38.62
	Mean number of clinical services offered directly	11.0	9.8
	Mean number of clinical services contracted to other entities	0.8	1.2
	Mean LHD service area FQHCs per 1,000,000 population	2.0	2.6
	Percent LHDs serving HPSA	74.7%	83.0%
	Mean LHD service area percent population Medicaid eligible	19.0%	19.9%
	Mean LHD service area unemployment	5.2%	9.1%
Institutional factors	Executive director has clinical background	43.7%	34.6%
	LHD executive director is full-time position	86.3%	91.5%
	LHD is governed by local board of health	74.4%	75.2%
	State-level governance	22.1%	26.7%
	LHD controls IT hardware purchasing decisions +	22.2%	
	Plans to seek accreditation within 18 months ++		8.3%

+ Information about IT hardware purchasing control was not ascertained in 2010
++ Information about accreditation plans was not ascertained in 2005

LHD Use of EHR in 2010 (*Research Question 1*)

We found substantial differences in EHR user versus non-user characteristics in 2005 than in 2010 (Table 5). In 2005, almost no LHD characteristics differed significantly (p < .05) for EHR users versus non-users. Two LHD characteristics—size of population served and per capita expenditures—showed substantively meaningful differences for users versus non-users, though these differences were not found to be statistically significant. Interestingly, despite previous studies that have limited analysis of EHR usage to LHDs providing primary care or oral health services, we found no difference in provision of those services between EHR users and non-users as of 2005. Bivariate comparisons for the three clinical service factors and the area level composite measure were performed (data not shown), and no between-group differences were found.

By 2010, however, significant differences between EHR users and non-EHR users emerged in several resource-based and institutional factors. Clinical services differences, for example, differentiated adopters and non-adopters by 2010, with EHR users providing a greater number of services and more frequently providing primary care and dental services than non-users. Perhaps the most dramatic difference appeared in LHD self-reported plans to seek accreditation, with nearly three-times the proportion of EHR users reporting such plans compared to EHR non-users.

Table 7: Bivariate comparison of EHR users versus non-users in 2005 and 2010

LHD or Area-Level Characteristic		2005 EHR Status Non-Users (n=294)	2005 EHR Status Users (n=113)	2010 EHR Status Non-Users (n=405)	2010 EHR Status Users (n=107)
Resource-based factors	Mean size of population served	199,363	235,609	200,903	244,274
	Proportion serving:				
	Urban	55.6%	44.3%	44.7%	55.1% **
	Suburban	15.7%	21.2%	17.8%	22.4%
	Rural	28.9%	34.5%	37.5%	22.4%
	Mean per capita expenditures	$32.10	$37.19	$35.82	$40.31
	Clinical Services:				
	Mean number of clinical services offered	14.1	13.7	12.7	14.0 *
	Percent providing primary care services	13.0%	10.5%	12.4%	14.0%
	Percent providing dental services	36.1%	25.7%**	30.0%	32.7%
	Mean number of clinical services contracted to other entities	0.8	1.1	1.4	1.2
	LHD Service Area:				
	FQHCs per 1,000,000 population	1.4	1.2	2.4	2.4
	Percent serving HPSA	77.9%	64.6%**	85.8%	81.3%
	Mean percent population Medicaid eligible	19.3%	19.3%	19.7%	19.0%
	Mean service area unemployment	5.1%	5.0%	9.3%	8.8% *
Institutional factors	Executive director has clinical background	52.7%	56.6%	45.4%	51.4%
	LHD executive director is part-time position	89.8%	84.1%	92.4%	94.4%
	LHD is governed by local board of health	72.5%	78.7%	73.6%	69.2%
	State-level governance	23.5%	22.1%	27.4%	21.5%
	LHD controls IT hardware purchasing decisions	24.8%	25.7%		
	LHD has plans to seek accreditation			7.4%	12.2%

* p < .1 ** p < .05 *** p < .01

These factors were examined simultaneously through multivariable logistic regression analyses, with odds ratios shown below in Table 6 and bootstrapped relative risks shown in Table 7. Adjusted probability of EHR use by number of clinical services provided is shown in Figure 2. (For additional logistic models, please see supplementary material.)

Table 8: Full multivariable logistic model predicting LHD use of EHR use in 2010

	LHD or Area-Level Characteristic	**Odds Ratio**	**p-value**
Resource-based factors	LHD size of population served (standardized)	0.98	0.81
	LHDs serving:		
	Urban	(*Ref.*)	
	Suburban	0.96	0.92
	Rural	0.36	< 0.01
	LHD per capita expenditures (standardized)	1.12	0.45
	Clinical Services+		
	Number of clinical services offered	1.16	0.02
	Number of clinical services contracted	0.97	0.65
	Communicable diseases factor	0.44	< 0.01
	Chronic condition screening factor	0.86	0.44
	Obstetrics factor	0.81	0.16
	LHD service area+		
	Poverty index factor	1.02	0.87
Institutional factors	LHD executive director has clinical background	1.20	0.49
	LHD executive director is part-time position	0.92	0.86
	LHD is governed by local board of health	0.90	0.76
	State-level governance of LHD	1.03	0.93
	LHD controls IT hardware purchasing decisions	0.87	0.64

+ Odds ratios shown correspond to a change in one standard deviation for each of the factor variables

The model reveals that the resource-based predictors were more strongly associated with EHR usage than the institutional factors, with none of the institutional factors were achieving significance in the model. One of the strongest relationships observed was between number of services offered in 2005 and EHR use in 2010. The number of clinical services offered by an LHD was positively associated with EHR use, even controlling for the nature of the services through the three clinical services factors. Interestingly, the only clinical services factor that was significantly associated with EHR use, communicable disease services, was negatively associated with use of EHR, with the other factors not significantly associated in the model.

Additional logistic models limited to those LHDs providing 1 or more clinical services, those providing and 5 or more, only those LHDs who provide primary care or dental services, and a model that removed two potential outliers all revealed nearly identical associations, suggesting that these findings are robust to LHDs that are more and less active in direct service provision (see supplementary material).

Table 9: Relative risks of 2010 LHD use of EHR for significant predictors from multivariable logistic model

LHD Characteristic	Relative risk for EHR Use
LHD serves:	
Rural versus Urban area	0.45 ***
Rural versus Suburban area	0.53 **
Number of clinical services provided:	
50^{th} vs. 25^{th} percentile (14 vs. 10 services)	1.64 **
75^{th} vs. 50^{th} percentile (18 vs. 14 services)	1.55 **
Communicable disease factor:	
Change from mean to 1 standard deviation below	0.61 **
Change from mean to 1 standard deviation above	0.54 **

$^{+}$ 95% confidence intervals bootstrapped using 1000 repetitions, percentile method shown
* p < .1
** p < .05
*** p < .01

The risk ratios suggest a potential issue with respect to an urban-rural EHR usage divide, with rural areas only 71% as likely to use EHRs as their urban counterparts, even after controlling for other relevant factors.

LHD Adoption and Abandonment of EHR (*Research Question 2*)

The study's second research question involved examination of EHR usage category in both 2005 and 2010 for the 106 LHDs for which data were available. In our sample, a large proportion of LHDs remained unchanged in their EHR use status (n=65 non-users and n=7 users) and others adopted EHR (n=10) between 2005 and 2010, all of which are to be expected. We also found evidence suggesting that a non-trivial number of LHDs reported abandoning EHRs (n=21) over that same time.

A closer examination of LHD responses indicates that there was substantial heterogeneity in response patterns between the two years for each department, as shown in Table 8. While some variation is to be expected, particularly from categories such as "Planning to implement" to "Implemented", other response patterns were also prevalent. For example, of the 31 LHDs that reported having EHRs implemented in 2005, only 7 reported still having EHRs implemented in 2010; a greater number reported having No Activity or that EHRs were Not Applicable.

Table 10: LHD EHR usage responses across years

		2010: Implemented	2010: Planning to implement	2010: Investigating or have investigated	2010: No activity	2010: Not applicable	Total
2005	Implemented	7	4	11	5	4	31
	Planning to implement	2	1	4	0	2	9
	Investigating or have investigated	5	6	9	8	1	29
	Aware	3	7	13	9	3	35
	Not aware	0	0	0	1	1	2
	Total	17	18	37	23	11	106

We explored the types of LHDs in each of these categories, we performed bivariate analyses shown in Table 9. The results of the bivariate analyses shown in Table 8 suggest that, while many of the differences were not statistically significant, a substantively meaningful pattern emerged.

As a whole, EHR users and EHR adopters look relatively similar while EHR non-users and EHR abandoners look more similar in their resource-based and institutional characteristics. These latter groups tended to serve fewer urban areas, spent less per capita, served higher-need areas, and were less likely to be pursuing accreditation than EHR users and adopters. Perhaps most notably, especially in light of findings discussed above in our first research question, LHDs that reported abandoning EHRs between 2005 and 2010 offered significantly fewer clinical services than other LHDs.

Table 11: LHD and area characteristics (in 2005) by EHR usage category

	LHD or Area-Level Characteristic (2005 values)	EHR Use Status (2005 to 2010) Non-User (n=65)	Abandoned (n=24)	Adopted (n=10)	User (n=7)
Resource-based factors	Mean size of population served	244,500	191,000	144,000	386,000
	LHDs serving:				
	Urban	53.9%	45.8%	70.0%	71.4%
	Suburban	12.3%	20.8%	20.0%	14.3%
	Rural	33.9%	33.3%	10.0%	14.3%
	Mean per capita expenditures	$38.53	$45.66	$53.80	$55.58
	Mean number of clinical services offered *	15.0	12.7	18.1	15.7
	Mean number of clinical services contracted to other entities	0.8	0.8	0.6	0.7
	Mean LHD service area FQHCs per 1,000,000 population	1.2	2.0	0.9	0.6
	Percent LHDs serving HPSA	81.5%	75.0%	60.0%	57.1%
	Mean LHD service area percent population Medicaid eligible	18.8%	20.5%	16.6%	17.6%
	Mean LHD service area unemployment	5.0%	5.3%	4.6%	4.5%
Institutional factors	Executive director has clinical background	50.8%	62.5%	70.0%	71.4%
	LHD executive director is full-time position	89.2%	83.3%	100.0%	100.0%
	LHD is governed by local board of health	73.9%	70.8%	80.0%	71.4%
	State-level governance	26.2%	33.3%	30.0%	14.3%
	LHD controls IT hardware purchasing decisions (2005)	24.6%	29.2%	30.0%	28.6%
	LHD plans to seek accreditation (2010)	7.7%	4.2%	20.0%	28.6%

* $p < .1$
** $p < .05$
*** $p < .01$

Changes in these baseline LHD and service-area characteristics were also substantively, though not always statistically significantly, associated with EHR use, adoption, and abandonment, as shown below in Table 10. EHR-adopting LHDs saw larger population increases than all others, while EHR users saw less population growth, albeit from a higher starting point in 2005 than any other group. EHR adopters provided, on average, one fewer clinical service in 2010 than in 2005. While this mirrors overall trends toward discontinuation of clinical services by LHDs (Hsuan and Rodriguez 2013), it is notable that LHDs that abandoned EHRs between 2005 and 2010 reported providing 0.1 more clinical services in 2010 versus 2005. EHR adopting LHDs also saw a greater change in service area unemployment rate than all other EHR categories.

Perhaps the most obvious differences appear in the two institutional factors shown in Table 10. A new executive director was significantly associated with EHR adoption. Although it was only borderline significant, EHR adoption also associated with change in governance, as no EHR-adopting LHDs also underwent a change in LBOH or state/local level governance arrangements.

Table 12: Change in covariates from baseline (2005) to follow-up (2010), by EHR use status

LHD or Area-Level Characteristic (Change from 2005 to 2010 values)		EHR Status (2005 to 2010)			
		Non-Users	Users	Abandoners	Adopters
Resource-based factors	% change in size of population served*	3.7%	1.7%	2.0%	4.1%
	% change in per capita expenditures	0.8%	8.8%	3.6%	0.0%
	Difference in number of clinical services offered*	-1.6	-0.9	0.1	-1.0
	Difference in number of clinical services contracted	0.4	0.1	0.4	1.0
	Percentage point change in FQHCs per capita	5.6%	0.3%	7.1%	11.6%
	Percentage point change in percent Medicaid eligible	-0.3%	-0.1%	0.2%	0.2%
	Percentage point change in percent unemployment	4.2%	3.1%	3.8%	4.5%
Institutional factors	New executive director *	44.6%	28.6%	25.0%	70.0%
	Change in governance (LBOH or state-level)	13.9%	14.3%	12.5%	0.0%

* $p < .1$

Multinomial logistic models also revealed few statistically significant relationships; this may be at least partially due to the relatively large standard errors due to the modest sample size. However, several relationships were strong predictors of EHR trends from 2005 to 2010, as shown in the plots of predicted probabilities (see Figures 2 – 4).

As the difference in number of services offered by an LHD grew (i.e., more services that an LHD reported adding between 2005 and 2010), the more likely that LHD was to report abandoning their EHR.

Other differences as shown in the figures may have substantive meaning but were not statistically significant and are not discussed here.

Discussion

This study's findings suggest that in both 2005 and 2010 approximately one-third of all LHDs reported having an EHR implemented or in the process of being implemented. The fact that overall use did not change appreciably between 2005 and 2010 runs contrary to trends toward increasing levels of EHR use in other healthcare settings during this time (Jamoom, Beatty et al. 2012). It also contrasts with NACCHO publications that, after cautioning about methodological differences between two reports, suggest EHR use by LHDs is on the rise (National Association of County and City Health Officials 2010). This study is the first to use consistent methods that enable cross-year comparisons and thus the first to suggest that LHD adoption of EHRs may not be increasing and, in fact, a non-trivial number of LHDs may have abandoned EHRs between 2005 and 2010.

The study's first research objective examined LHD use of EHR in 2010. Our findings related to clinical services presented an interesting paradox. The number of clinical services was positively associated with EHR use, while scales measuring provision of specific services were not. LHDs with greater communicable disease services were less likely to use EHR; chronic disease screening and obstetrics services were not associated with EUR use. We interpreted this to mean that the LHD's general orientation toward clinical services helps drive EHR use, rather than a specific focus on any given clinical area. An alternative hypothesis is that there are specific services that were not included in the three factors in our analysis that were positively associated with EHR use and were responsible for the overall association seen between number of services and EHR use. If provision of that hypothetical bundle services is negatively correlated with provision of communicable disease services, that could explain this seemingly divergent finding. We also explored the clinical services-EHR usage relationship further in the supplementary material at chapter's end.

We also found evidence that LHDs serving poorer and rural areas are less likely to be EHR users, suggesting a potential digital divide for those LHDs and the populations they serve that mirrors trends in other healthcare settings (DesRoches, Worzala et al. 2012).

These categories, which we broadly refer to as resource-based factors, were relatively stronger predictors of EHR use than several characteristics related to LHD leadership and governance. We originally hypothesized that LHD with greater control over IT acquisition and with more local levels of governance may be more likely to adopt EHR. Our results suggest that there is little to no effect of these factors as measured in our study. This suggests that the governance and over institutional factors that were previously shown to be modestly correlated with health IT use (Vest et al., 2012) may be less important in EHR usage decisions than the LHD's budget and service profile (e.g., number and types of clinical services) and where that department is located (urban versus rural).

Of the subsample of LHDs with two years' of NACCHO Profile data, there was substantial variation in reported use of EHR between 2005 and 2010. Nearly two-thirds of departments reported not using EHR in either 2005 or 2010 while less than 10% reported using it in both years. This finding contrasts with earlier studies suggesting sizable gains in the proportion of LHDs using EHR (National Association of County and City Health Officials 2010). Previous studies may have overstated EHR use by limiting LHDs sampled to those more likely to be users, or may have had differential response from EHR using versus non-using departments given that the study centered on public health informatics. Our findings may therefore represent a truer picture of trends in EHR adoption and use than previous studies. It also suggests that studies offering a one-time snapshot of EHR use in LHDs may be missing larger trends in EHR adoption and abandonment.

In attempting to understand reasons for the relatively low adoption and retention rates, especially given trends in other parts of the health system (Hsiao, Hing et al. 2010), we analyzed four types of EHR use statuses: non-users, users, adopters, and abandoners.

The characteristics of the LHDs in each of the four EHR usage categories (non-user, user, abandoners, and adopters) suggested that LHDs who were EHR users and those who were EHR adopters appear quite similar in many respects while non-users and abandoners appear more similar in these same respects. For example, users and adopters both generally serve larger and more urban populations and provide a greater number of clinical services than non-users and abandoners. One possible explanation for this was that users and adopters are in reality somewhat similar but the lag in adoption can be explained by the substantively lower proportion of adopter LHDs that are governed at the local level as opposed to the state level, as state governance and control over decision making has previously been shown to be positively associated with IT adoption at LHDs (Vest, Menachemi et al. 2012).

As with our examination of EHR use in 2010, we found evidence to suggest that the resource-based predictors were more strongly associated with EHR adoption and abandonment than were the institutional predictors.

In bivariate analyses, we found that LHDs that abandoned EHRs were the only group to report adding clinical services between 2005 and 2010. The addition of clinical services is especially notable given secular trends towards discontinuation of clinical services by LHDs during this period (Hsuan and Rodriguez 2013). We attributed this shift to a possible strategic reorientation within the department away from EHR-relevant services and towards a broader number of non-EHR relevant services. The theory that EHR implementation costs crowd out spending that would otherwise be directed to clinical services was not borne out (i.e., they did not report a differentially high level of clinical service discontinuation). Instead, LHDs that used EHR in both 2005 and 2010 saw substantively larger gains in expenditures than other LHDs. This is all the more meaningful given that they also started from the highest baseline per capita expenditures in 2005. The contribution of EHRs to this increase in spending is not known, though given that spending was flat between 2005 and 2010 for adopters, implementation costs are unlikely to be an issue.

LHDs that reported adopting EHRs between 2005 and 2010 or using in both years tended to be located in areas that saw the lower gains in unemployment rates during that time. We had originally presumed that this type of change in area level needs would be negatively associated with EHR adoption as LHDs may be facing increasing service demands and budgetary constraints. The alternative hypothesis is that the increasing area-level deprivation may contribute to an increasingly central role for the LHD provision of clinical services, so investment in EHR may be a strategic opportunity to better coordinate care for patients served by LHD providers.

The sole institutional factor significantly associated EHR adoption was a change in LHD executive director, with new directorship significantly associated with EHR adoption. This is a potentially important finding as it underscores the importance of leadership in the EHR adoption process. If we are to seek additional use of EHR by LHDs, interventions aimed at promoting adoption might be targeted to LHDs undergoing a change in execurive director or those with new leadership.

Accreditation-seeking LHDs were substantively more likely to be users of EHR in both 2005 and 2010 or to have adopted EHR by 2010, though these differences were not significant. The fact that EHRs can be used to meet at least one of PHAB's accreditation guidelines (Public Health Accreditation Board 2013) suggests that it would be unlikely for accreditation-seeking LHDs to abandon EHRs. This appears to be visible in the relatively lower proportion of EHR-abandoning LHDs who plan to seek accreditation. However, since there are only two points of data, it is not known whether accreditation plans or EHR discontinuation preceded the other. There is not a clear enough pattern to discern whether it is not common for LHDs to adopt EHRs in conjunction with their accreditation plans.

A multinomial logistic regression to simultaneously assess the association between a select subset of resource-based and institutional predictors did not reveal many significant relationships. A change in the number of services offered was associated with EHR abandonment, though the effect is rather small and requires a dramatic change to have a significant effect on the probability of abandoning EHR. As further data becomes available, this area may benefit from additional analyses. Additional waves of data will also help shed additional light on the temporal issues resulting from only having two waves of data and an inability to determine sequential order of changes observed in the variables.

Limitations

The study results should be viewed in light of some limitations. The study data are self-reported data and with any such study there were obvious limitations of our ability to ascribe causality. But the study's two research questions did not seek to make equivocal causal statements. Rather the study aimed to identify the types of LHDs using EHR and the potential underlying motivations for EHR adoption and use.

The fact that NACCHO Profile data are self-reported presents three potential sources of bias: those related to sampling, questionnaire construction, and administration (Bourque and Fielder 2003). Sampling biases are mitigated by the study's universal sampling frame and extremely high response rate (80% in 2005 and 82% in 2010). NACCHO has previously addressed potential questionnaire construction biases and have revised Profile data collection instruments to mitigate these biases (National Association of County and City Health Officials 2006). One area of concern for this study, however, was administration biases such as a lack of control over who responds. A given LHD respondent may provide inaccurate information in one year or for one specific programmatic area while a second respondent provides accurate information another year or programmatic area. We examined this potential source of bias by including variables for concepts that are unlikely to vary in the study's five year range (e.g., state-level governance status) and found virtually no intra-LHD variability. We assumed that this fidelity was also reflected in other measures for all LHDs.

The study's sample was limited to LHDs that completed specific modules in the 2005 and 2010 NACCHO Profile surveys. To explore potential variations in the sample, we examined EHR-module respondents versus non-EHR module respondents in both 2005 and 2010 (as shown in table A3) but did not find evidence of substantively important between-group variation. Thus given the Profile's high response rates and the lack of substantial variation in observable characteristics between EHR-respondent LHDs and non-EHR respondent LHDs, we did not include any sample selection techniques in our analyses. This is consistent with other published research using this dataset and methodology (Grembowski, Bekemeier et al. 2010).

As a secondary analysis of existing data, many of the study's conceptual measures relied on imperfect proxies. For example, exploration of the impact of mimetic isomorphic forces may have benefited from additional information about the use of EHR by community partner organizations and other LHDs with whom a given LHD collaborates and communicates ("professional norms"). If we assume that a perfect measure of LHD partner use of EHR is positively correlated with an LHD's own use of EHR and that having a full-time director makes these partnerships more likely, then the negative association between LHD director's full-time employment status may be conservatively biased toward the null. This may in part explain why several of the hypothesized institutional predictors were insignificant in the multivariable models.

The study included a set of clinical services in all analyses. While this set was previously validated (Hsuan and Rodriguez 2013), no study has directly determined an exhaustive list of services—clinical or otherwise—that are relevant to an EHR at LHDs. Further exploration of additional services beyond the 29 clinical services examined did reveal additional services (e.g., syndromic surveillance) with bivariate associations with p-values below the 0.05 threshold. However, as the study's dataset did not contain data on how the EHRs were used, these analyses were not conceptually driven and were subject to multiple testing biases and are not presented here.

The study's multitude of coding and analytic sample refinement decisions were also potential sources of bias. The sensitivity of findings to these decisions is explored above in the Sensitivity portion of the Methods section.

Conclusion

LHD EHR use has remained at a relatively low and declining level from 2005 (27.8%) and 2010 (20.1%). The study has, for the first time, found evidence that suggests that there is a considerable amount of churn in LHD use of EHR, with approximately one-quarter of LHDs reporting abandoning use of an EHR between 2005 and 2010 while only approximately 10% report adopting. To the extent that policy makers are interested in increasing the level of EHR use by LHDs, it is therefore necessary to think about ways in which to promote both adoption and retention of EHRs by LHDs. Future work to identify the reasons for EHR abandonment could greatly benefit this effort.

This study also identified several resource-based characteristics that are associated with EHR usage. Based on this, we might conclude that strategies aimed at further promotion of EHR use and adoption would be better suited to target LHDs already providing a large number of clinical services, for example, as opposed to dissemination efforts aimed at promoting EHR use through professional networks or other learning collaborative-type efforts. One notable exception to this is that a new executive director is often associated with EHR adoption and may therefore offer an opportunity to target adoption efforts.

One particularly important conclusion from this study is the lag of rural LHD usage of EHR compared to their urban counterparts. Whether this difference is due to rural LHDs seeking EHRs being unable to obtain them, due to EHRs being of lesser utility to these rural LHDs, or to other reasons entirely is unknown. This potential disparity may benefit from further inquiry

The characteristics found to be associated with adoption and abandonment of EHRs over time also shed valuable light in several areas, specifically with respect to the fact that abandonment of EHR is associated with an increase in the number of clinical services provided. Over time and as additional data become available regarding EHR use, adoption, and abandonment, these analyses may benefit from another look.

If an increasingly fully wired public health system is a goal, we face twin challenges of spurring non-users to adopt EHR and subsequently doing more to ensure that users of EHR retain those systems. Purposive sampling of LHDs that have adopted and retained versus those that have adopted and not retained their EHR systems is a likely first step in understanding the forces at play in initial adoption decisions. Undertaking policy measures aimed at spurring adoption are likely to be more successful if targeted towards resource-based aspects of LHDs, or to LHDs with similar resource-based characteristics, than others targeting institutional or isomorphic factors. But any gains in EHR adoption may be transitory unless we learn more about the drivers of EHR retention at LHDs.

FIGURES

Figure 4: Conceptual Model for LHD Adoption and Abandonment of EHR

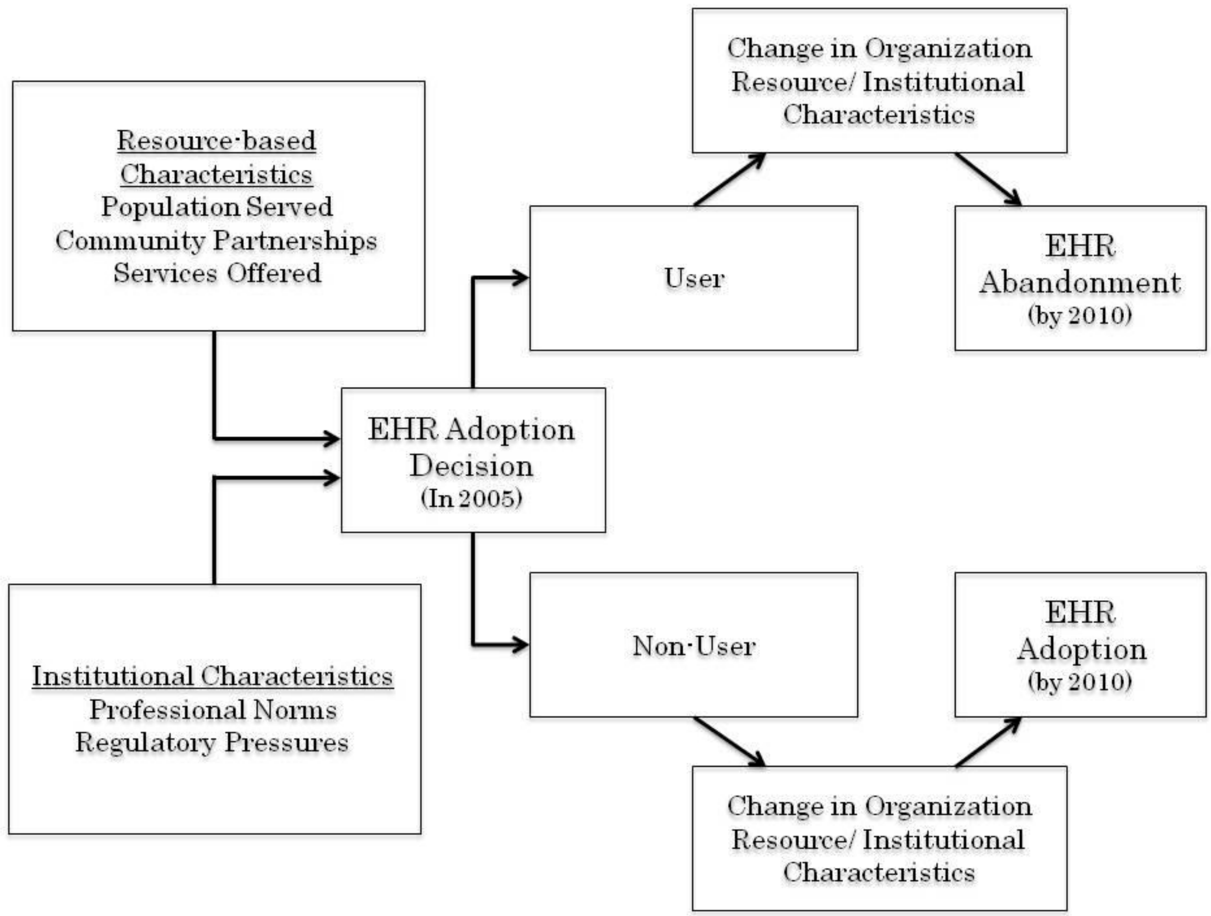


Figure 5: Probability of each EHR category by change in number of services offered

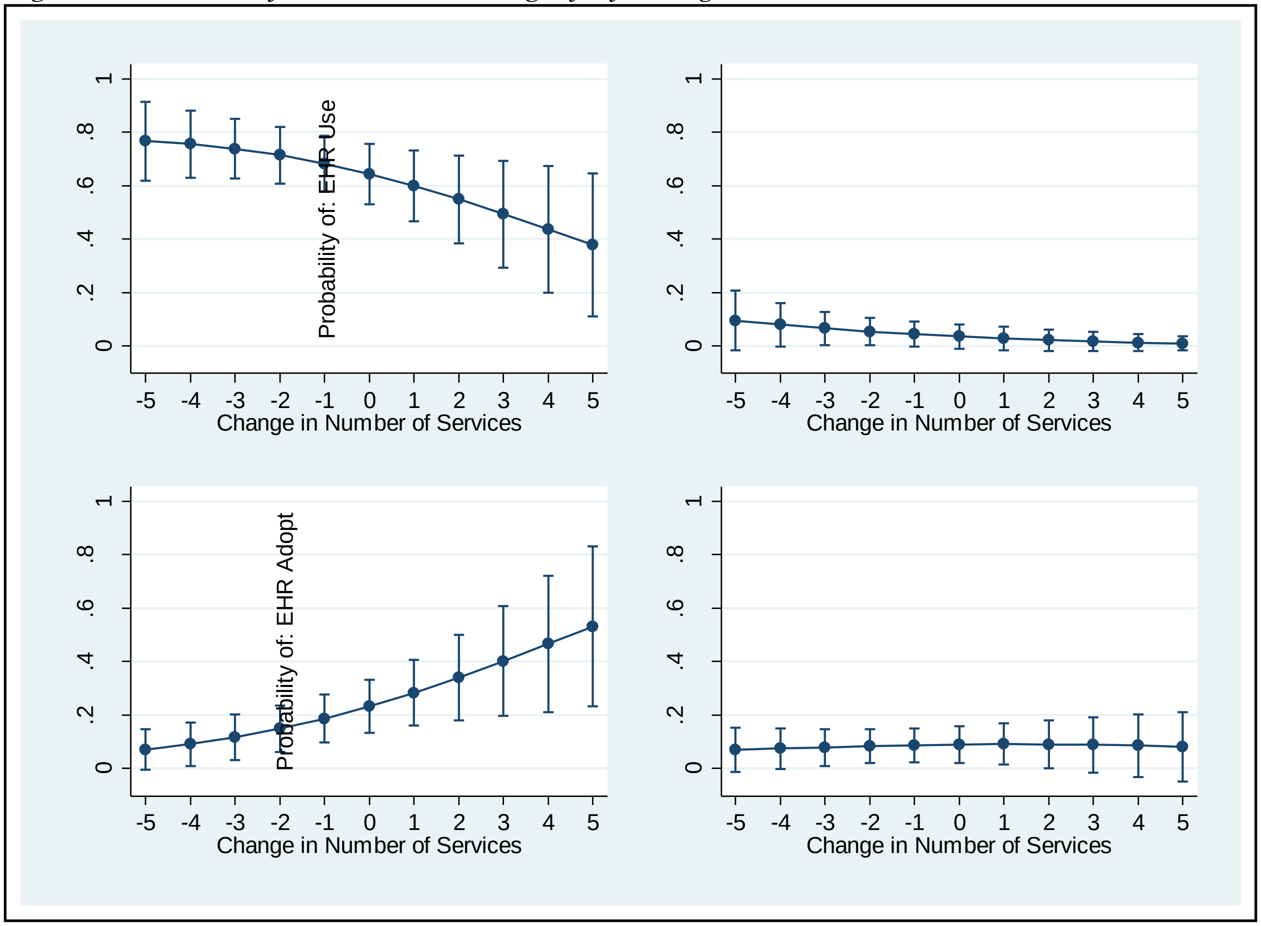


Figure 6: Probability of each EHR category by change in per capita expenditures (%)

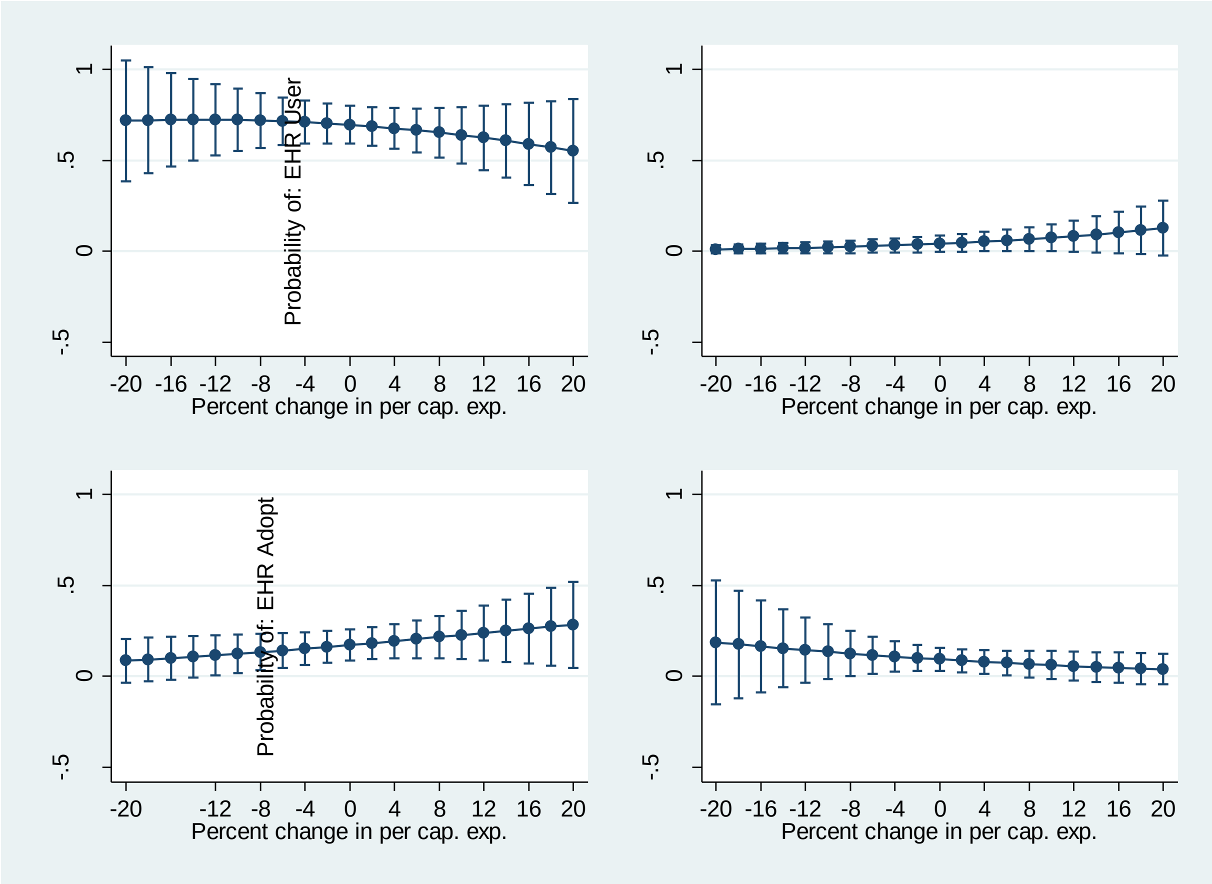
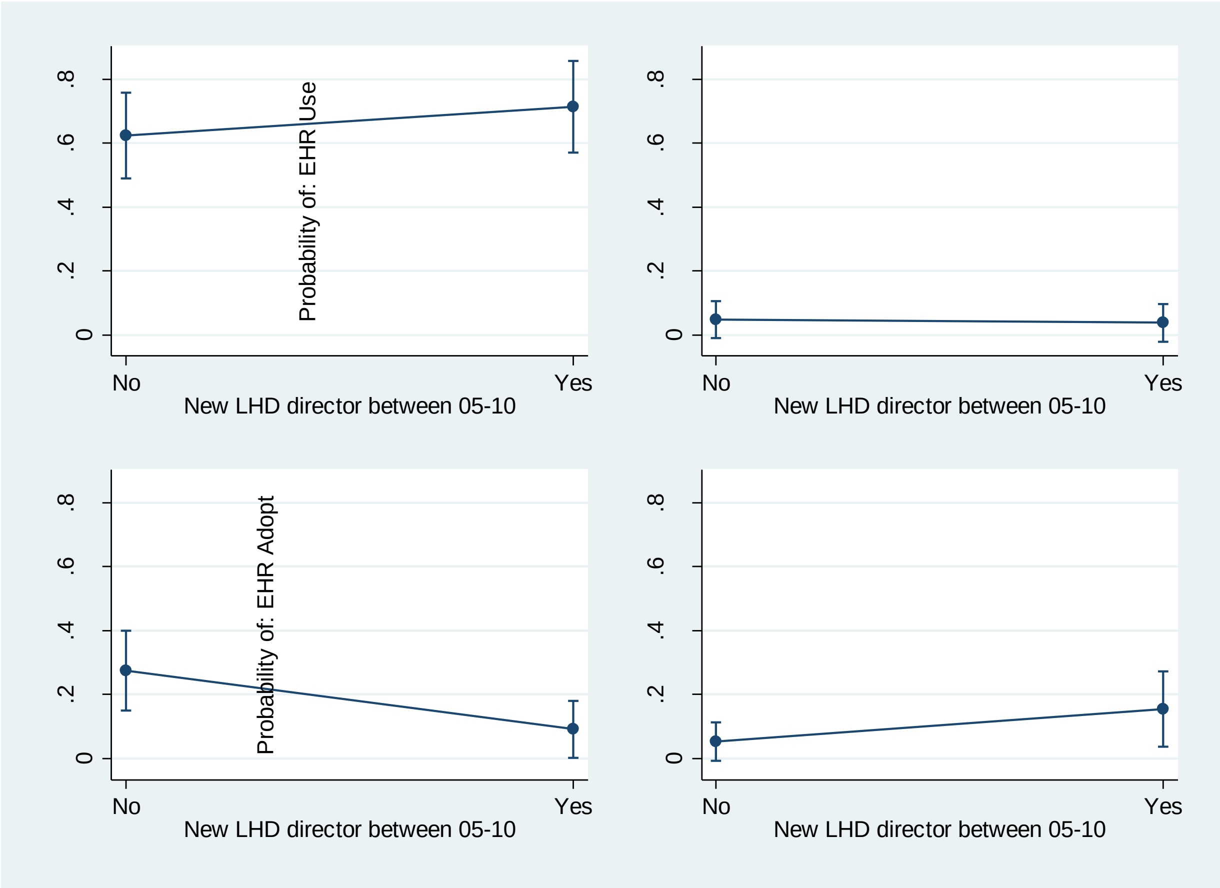


Figure 7: Probability of each EHR category for LHDs with and without new executive director



Supplementary Material

Supplemental Literature Review

As briefly outlined in the main chapter, the main information reported to date regarding LHD use of EHR comes via point estimates from single-year samples of LHDs (National Association of County and City Health Officials 2009; National Association of County and City Health Officials 2010). The most detailed report to date focuses on public health informatics and devotes a module to EHR use in LHDs. The report finds that, of the 86 LHDs queried, approximately half use an EHR. This contrasts However, this report These methodological differences may have overstated the differences between use of EHR between 2005 and 2010. First, the 2005 Profile was a random sample of all LHDs whereas the 2010 report focused only on LHDs providing primary or dental care services. Second, the 2010 report's wording for the primary care provision question is broader than the 2005 Profile report's (which asks specifically about "comprehensive primary care" services), so it is difficult to limit the 2005 Profile sample to similar LHDs. Third, the 2005 Profile sample represents a broad range of LHDs that completed a survey on a range of informatics and non-informatics issues where as the 2010 report was limited to informatics-related topics. It is possible that response bias may have made informatics-attuned LHDs more likely to respond to the 2010 report whereas this bias may not impact the 2005 Profile.

In short, a direct comparison of the NACCHO Profile data and the 2010 informatics report is not feasible. What we are left with, therefore, are separate cross-sectional datasets that reveal very little about secular trends in LHD adoption and use of EHRs. The scholarly literature does not contain any data on trends on trends over time either. The lone peer-reviewed study regarding LHD use of EHR is a cross sectional analysis of data from the

2008 NACCHO Profile that examines the effect of LHD governance on use of information technology (Vest, Menachemi et al. 2012). That study developed a four-point scale to assess information technology (IT) usage; one of the technologies included in this scale was EHR (the others included health information exchange, mobile information technology, and wireless networks). The study concluded that LHD organizational characteristics were associated with its IT scale score, but did not specifically comment on EHR adoption beyond this scale score.

Independent Variables & Covariates—Description, Coding, and Data Sources

For a complete overview of the independent variables used to address the study's first and second research questions see Table A1 and Table A2, respectively.

Resource-Based Variables: A total eight resource-based variables were included in analyses.

First, the LHD's service-area population served, as reported by the LHD to NACCHO. This measure was also used to calculate per capita measures where applicable.

Second, LHD per capita expenditures were calculated by dividing LHD total expenditures by size of population served, as reported by LHDs to NACCHO. The log of per capita expenditures was used in models to minimize skewness. Values from 2005 were adjusted to 2010 dollars using the general consumer inflation index (U.S. Bureau of Labor Statistics 2012) to facilitate cross-year comparison.

The number of LHD full time equivalent employees was considered as a potential predictor variable but was excluded due to multicollinearity issues with LHD per capita expenditures.

The fourth resource-based variable measured LHD service area-level characteristics. As above, an exploratory factor analysis was conducted, this time using four area-level variables obtained from the ARF dataset. Methodologies for obtaining area-level estimates from the ARF and reconciling county-level data with LHD jurisdictions are detailed below

The number of Federally Qualified Health Centers (FQHCs) in the service area was calculated by dividing the total number of clinics by the total area population; throughout the study it is presented as a number per 10,000 population. It was hypothesized that LHDs serving areas with fewer FQHCs may be more likely to use EHRs due to a potentially larger role played in the safety net in their communities.

A dichotomous variable was constructed to indicate whether any part of the LHD service area was a HPSA for primary care. It was hypothesized that LHDs serving such areas may be more likely to report EHR usage due to fewer external providers available in the community and a potentially stronger role for the LHD in the safety net.

The percent of the LHD service area population that is eligible for Medicaid was calculated. The total number of Medicaid eligibles was divided by the total population for the entire LHD service area. It was hypothesized that as the percent of population eligible for Medicaid increased, LHDs may be less likely to adopt EHR both because of the signaled decrease in area-level resources and perhaps the stronger role played by providers focusing on the Medicaid population and a decreased role played by the LHD.

The unemployment for the LHD service area was included. It was hypothesized that as the unemployment rate increased, LHDs may be less likely to adopt EHR because of fewer area-level resources on which for the LHD to draw and, overtime, the inability of these LHDs to make large investments of the kind required to adopt and use EHRs.

Since the HPSA measure is dichotomous, a factor analysis with a varimax rotation was conducted on the polychoric correlation matrix of four area level measures from 2005 was conducted with a varimax rotation (Kolenikov and Angeles 2009). A single factor was retained (Eigenvalue 1.16), referred to here as the area's poverty index, that loaded much higher onto percent Medicaid eligibles (0.72) and percent unemployment (0.68) than onto per capita FQHCs (.20) and HPSA shortage area (0.22). A single measure was then created that averaged the

A separate factor analysis of the change in area-level measures from 2005 to 2010 (or closest years available) was conducted. However, no factors were retained as none had an Eigenvalue greater than 1.

The final resource-based variables pertain to public health service provision by the LHD. The NACCHO dataset has information on 75 public health services. While there is no universally accepted methodology for measuring or counting public health service provision, one recent study pared the list of 75 services down to 29 clinical services (Hsuan and Rodriguez 2013). This study used this same set of 29 relevant clinical services to proxy for EHR-relevant public health service provision.[d] For the purposes of this study, since we were conceptually interested in the relative amounts of activities and services provided by departments themselves versus those contracted to others versus those performed by someone else within the community, the total number of activities and services provided by each of these sources was be entered into the model as a count (maximum possible for each

[d] There are few peer-reviewed categorizations of LHD services into 'clinical' or 'EHR-relevant' versus those that are not. Broadly speaking, for the purposes of this study 'clinical' refers to services other than non-clinical services such as environmental health or emergency preparedness-type services. Further work to more formally identify and define this breakdown is likely a worthwhile effort and something I have considerable interest in pursuing in the future.

29). This service-count measurement methods was also used in the most relevant peer-reviewed study to proxy for service provision activity (Vest, Menachemi et al. 2012).

An exploratory factor analysis was conducted to identify clusters of clinical services that tended to co-occur together in the sample LHDs. Since the service measures are dichotomous, exploratory factor analysis with a varimax rotation was conducted on the polychoric correlation matrix of the data. As shown below in Table A3, three factors were identified, all of which had Eigenvalues greater than 1.5. Three additional factors with Eigenvalue greater than one were not retained due to having only one service each with high loadings. Based on these analyses, three separate service scale scores were generated by averaging an LHD's number of services with loadings of 0.7 or higher for a given factor.

A separate factor analysis was conducted to measure change in services between 2005 and 2010 for the study's second research aim. Three factors were retained for consideration in a final EHR adoption model as shown below in Table A4, each of which had an Eigenvalue greater than 1 and conceptually similar services with high factor loadings. A fourth factor with Eigenvalue greater than one (1.25) was not retained because the services with high loadings were not conceptually similar and thus would not facilitate analysis of the study's research objective.

Institutional Variables: In addition to the resource-based variables, five variables were identified based on the institutionalism theories discussed in the methods section above.

First, based on data from the NACCHO dataset, an indicator variable was constructed for whether the director of an LHD has a clinical background. This measure was identified in a previous study as a good measure of health department service orientation and performance (Bekemeier, Grembowski et al. 2012).

Second, an indicator variable was included for whether or not the LHD is overseen by a local board of health, as reported to the NACCHO Profile.

Third, an indicator variable was included for whether the LHD is governed locally or at the state level, as reported to the NACCHO Profile.

Fourth, LHDs self-reported their plans to seek accreditation under the PHAB to the NACCHO Profile. An indicator variable was added to the model for whether or not the department has plans to seek accreditation within the next 18 months. This proxy was chosen instead of the more general question of whether they have any plans to seek accreditation because the non-time limited version of the question was more aspirational whereas the time-limited version applies more to departments who have actually started planning for accreditation (and therefore would have been subject to its institutional forces). Data for this measure is only available in the 2010 survey because the LHD accreditation process had not yet been implemented in 2005.

Fifth, an indicator for whether the LHD alone (as opposed to the state, county, city, or some combination thereof) controls IT purchasing was created.

For the study's second research aim, many of the variables outlined in the conceptual model specification table in Table A2 (see tables at end of supplementary material) rely on identifying changes between baseline and follow-up measurements. For the purposes of this study, baseline measurements are taken from the 2005 NACCHO Profile dataset and 2005 (or closest year available) ARF data. Follow-up measurements are taken from the 2010 NACCHO Profile dataset and 2010 (or closest year available) ARF data. Changes, either raw or percent, are calculated for the variables as constructed using methodologies described above.

Model Building & Missing Data

Model Building

Both conceptual and empirical tools were used to develop the final for the multinomial EHR adoption model. Specifically, the following process was used to develop the final multinomial logistic model. Predictor variables with little variation between baseline and follow-up (e.g., urban-rural status, change in number of clinical services contracted, percentage point change in Medicaid eligibles) were excluded. Next, for conceptual measures with multiple proxies, a single proxy was retained (the percentage point change in unemployment was retained while the percentage point change in FQHCs per capita was removed, the variable for new executive director was retained while the local board of health governance change variable removed). In both cases, the retained variables were also hypothesized to be stronger proxies for their respective measures and had more robust variation between groups. A multinomial regression model with the remaining variables was run and variables that were not at least borderline significantly associated with any of the four outcomes were not retained. Exploratory work was also performed with variables not included in the initial models and with any particularly promising or interesting findings.

Missing Data

Urban/suburban/rural data were missing for 1 LHD in 2005 and 95 LHDs in 2010. For 2005, the 1 LHD was manually located and coded to the appropriate classification (rural). For 2010, since the NACCHO data contains ZIP code information for LHDs, these 95 LHDs were manually matched to Rural Urban Commuting Area (RUCA) codes to estimate their rurality. RUCA codes were then converted into a three category urban-suburban-rural variable using the same coding definitions used in the original NACCHO dataset.

The other covariates for which there were non-trivial counts of missing data were LHD expenditures. A total of 96 LHDs were missing expenditure data for 2010. For LHDs with expenditure data from one year but not both (n=76), per capita expenditures for the missing year were set to the value from the available year. This allowed for reasonable approximation of LHD resources for a given year and also meant that the LHD would not register a change for the adoption models in the study's second part. Where no expenditure data were available (n=57), LHD per capita expenditures were set to the median value for the sample.

In addition, 2 LHDs were missing LBOH info for 2010. Through LHD responses to other survey questions it was apparent that both did indeed have LBOH and were re-coded accordingly. For full-time executive director, 7 LHDs were missing data for 2005 and 3 were missing for 2010. Since full-time director is by far the more common arrangement (> 90% of LHDs), with the exception of one LHD, the others were coded as having full-time executive directors. The one exception was a 2010 LHD who responded that they did not have a full-time director in 2005. Since change in full-time status was extremely rare in this dataset, the 2010 value was set to the 2005 value where possible.

Area level data were not matched for 19 LHDs in 2005 and for 9 LHDs in 2010. The missing values for each LHD were set to the corresponding median value for each variable in each year.

Additional Analyses & Sensitivity Analyses Performed

Longitudinal Modeling

This study employed two waves of data on each LHD so longitudinal analyses techniques were considered. It is reasonable to suspect that an LHD's health IT usage patterns in wave 1 (2005) are correlated with its usage patterns in wave 2 (2010). However, statistical controls for this correlation would reduce the very thing that this study seeks to exploit: instances when the two measurements are *discordant* rather than concordant. Given that the measure used is categorical rather than continuous and initial analyses reveal that a substantial proportion of LHDs reported different levels of awareness/use of health IT between wave 1 and wave 2, longitudinal modeling (e.g., random effects, autoregressive modeling, etc.) was not employed.

Survey Weighting

Despite the fact that the NACCHO Profiles are a virtual census of U.S. LHDs, differential inclusion of LHDs serving large populations in each module produces a dataset that may over-represent large health departments. NACCHO provides survey weights to make the data generalizable to the LHD population. However, this study does not seek to provide estimates of such nature. Rather, the study focuses on organizational predictors of EHR adoption and abandonment. For such studies it is only necessary to employ survey weights if we believe that the regression coefficient estimates would differ significantly according to the differentially over- or under-represented characteristic (DuMouchel and Duncan 1983). NACCHO Profile reports oversample based on size of LHD population served (National Association of County and City Health Officials 2011). LHD size of population served may or may not be a significant predictor for the study's research question, so two regressions were run on the final model—one with survey weights and one without. There were no changes between the two models (in terms of significant variables). Given a statistical preference against using survey weights in multiple linear regression models (Winship and Radbill 1994), survey weights were not used in this study.

Sensitivity Analyses

Where possible, this study relied on established methods and measures to construct and interpret the analytic dataset. In some cases, no such methods or measures have been established. To examine the sensitivity of the study's findings to classification, coding, and other decisions, a series of sensitivity analyses were performed.

To examine the sensitivity of findings to the construction of the outcome variable, models were replicated with an alternative outcome variable that only considered LHDs to be users of EHR if they reported already implemented EHR system (those who had begun implementation were counted as non-users). As shown in Table A5 below, while point estimates and the significance of a few variables changed, overall results suggest that the logistic model predicting LHD EHR use in 2010 was not sensitive to this coding decision.

As discussed above, previous reports on EHR use by LHDs was limited to those LHDs that provided primary care or dental services (National Association of County and City Health Officials 2010). Exploratory analyses with this study's full analytic dataset revealed a substantial number of LHDs that reported not providing either primary care or dental services in 2010 but who did report using EHRs in 2010, as shown in Table A6 below.

As this study was primarily interested in predictors of EHR adoption and use, LHDs who reported using EHRs were retained wherever possible to avoid potentially biasing findings because of exclusion criteria. A similar concern was that EHRs may be much less relevant for LHDs that do not have any clinical activities whatsoever. However, assuming that clinical services are themselves the drivers of EHR relevance is problematic to the institutional predictors included in the study's conceptual model. Therefore, sensitivity analyses compared findings for models run only on the full analytic sample (n=514), the subsample of LHDs who reported providing at least 1 clinical service in 2005 (n=393), and the subsample of LHDs who reported providing either primary care or dental services (n=176). A comparison of odds ratios and p-values for coefficients across all three models is shown in Table A7.

While it is potentially problematic to directly compare coefficients across logistic models using different samples (Allison 1999), these sub-sample models suggest that the overall model is not sensitive to the inclusion or exclusion of LHDs that do not report engaging in any clinical activities, as there are no substantial differences between model 1 and model 2 coefficients in terms of direction, magnitude, or significance. However, model 3 (LHDs engaging in primary care/dental services only) results were appreciably different for many predictors. Coefficient estimates for several variables may suggest distributional issues in the data (OR = 1586 for LHD service level unemployment, for example) that are not present for the full sample. Considering this in conjunction with the narrowing applicability of the study's findings should the more restrictive (model 3) sample be employed, we chose to retain the full sample (model 5, n=514) for subsequent analysis.

Next, to examine whether findings were robust to the study's definition of EHR adoption, sensitivity analyses were performed that limited the definition of 'adopters' to those who have already implemented and counted those who are planning to implement as non-adopters. For the majority of predictor variables, this coding change did not change the significance of the findings. Interestingly, in both the logistic regression model for research question 1 and the multinomial logistic regression model for research question 2, the LHD's service-area percent unemployment was statistically significant using this alternative outcome variable specification but not the primary specification. This is discussed in the limitations section above.

Analyses were also conducted to look for evidence of distributional or multicollinearity issues in the analytic dataset, particularly for governance variables and among the four area-level variables. Regarding the area-level variables, none had a pairwise correlation higher than 0.5 and further diagnostics, including goodness of fit and collinearity tests, did not reveal multicollinearity to be problematic. Regression models were also re-run that iteratively excluded each of the four area-level variables and findings did not change appreciably. The two variables that were found to be multicollinear were LHD per capita expenditures and LHD FTEs per 10,000 population (correlation 0.76, variance inflation factor > 4). Because these two variables are proxies for the same concept (population served – resources), one was excluded. Per capita expenditures was retained due to this being a potentially wider measure of LHD resources than FTEs, which might even be considered as resultant to expenditures.

To examine the sensitivity of findings to the study's imputation methods for missing data, models were re-estimated in two different manners. First, by using alternative logical imputation specifications. Namely setting the 95 LHDs with missing rurality data to suburban (often a catch-all category between the conceptual extremes of urban and rural) and setting all LHDs to median per capita expenditure level. While these alternative classifications did impact some findings for individual variables, they did not change the majority of findings nor the study's overall conclusions. A second approach was to use complete case analysis that excluded LHDs with missing data (n= 393 versus n=514 in the full model). Again this did not change the majority of findings nor the study's overall conclusions

Consideration was also given to the methods used to identify the analytic sample. Table A7 shows a comparison of characteristics of LHDs in the final EHR adoption-abandonment sample (n=106), LHDs with EHR usage data for 2005 (n=407), LHDs with EHR usage data for 2010 (n=514), with all other LHDs in the NACCHO dataset who do not have EHR usage data for either year (n=2193). Several categories did differ for the EHR sample versus non-EHR respondents, though these differences were largely due to NACCHO's stated oversampling, and differential follow-up, of health departments serving larger communities for module questionnaires (National Association of County and City Health Officials 2011). These differences are noted and expanded upon in the paper's limitations section.

In a related analysis of the impact of our decision to include all LHDs, regardless of number of clinical services provided, we re-estimated the logistic regression model predicting EHR use in 2010 for: LHDs providing at least one clinical service, LHDs providing at least 5 clinical services (the 25th percentile value for the sample), and LHDs providing at least 17 clinical services (the 75^{th} percentile value for the sample). As shown in Table A8, overall findings were not sensitive to this sample construction decision as model estimates did not change substantively. For Model 3, given that the point estimates remain very similar to the first two models, the lack of significance for many of the variables in the third model is more likely due to the larger confidence intervals for the reduced sample size than a true change in association.

We also examined subsamples of the data that examined: all LHDs (original sample), only those LHDs that provide any clinical services, and LHDs that provide primary care and or dental services—the inclusion criteria used when assessing EHR use in the 2010 NACCHO health informatics report (National Association of County and City Health Officials 2010). Again, the majority of the estimates were not sensitive to these sample inclusion decisions as very few estimates changed in direction, magnitude, or significance. One interesting exception is that state-level governance became highly significant in the model including only LHDs providing primary care or dental services.

While the study employed a lagged regression approach that used LHD characteristics from T_1 (2005) to predict EHR usage at T_2 (2010), additional consideration was given to the value of alternative predictor-outcome year specifications. Two additional models were thus run to test the sensitivity of findings to model year specifications. As shown in Table A10, we were much more successful in modeling LHD use of EHR in 2010 (models 2 and 3) than in 2005 (model 1). Indeed, the overall chi^2 test for model 1 was not significant while it was highly significant for models 2 and 3. Therefore, in addition to the conceptual rationale discussed in above, LHD EHR usage status was not added as a separate analysis in the main body of the chapter. According to Diffusion of Innovation theory, it is possible that the LHDs who were using EHR in 2005 were "early adopters" who could be differentiated from non-early adopters mainly through their innovativeness (Rogers 2003), a concept not reflected in the measures in the models below.

Clinical Services & EHR Usage

Because of the seemingly paradoxical finding that higher number of clinical services was associated with higher likelihood of EHR usage in 2010 but that greater number of communicable disease services offered was associated with lower likelihood of EHR usage, we performed additional analyses to examine patterns of service provision and EHR use among the LHD sample.

A closer examination of the proportion of EHR use across the spectrum of number of clinical services provided revealed no strong trends, as shown in figure A1.

We then analyzed the patterns of service provision for the 7 services comprising the communicable disease factor, as shown in Table A11. An informal hierarchy of service provision patterns appeared to emerge, with LHDs providing the a given number of services generally tending to provide the same services (e.g., those providing only one service provide tuberculosis screening, those providing two services provide both screening and treatment for tuberculosis, and those providing six services providing all services in the communicable disease factor except for HIV treatment). LHDs only providing one service out of the seven total services included in the communicable disease factor were also meaningfully, though not statistically significantly, more likely to be EHR users in 2010. This may help explain why EHR usage did not increase along with score on the communicable disease factor increased.

Table A1: Conceptual Model Specification for Research Aim 1

Organizational Theory	Theoretical Variable	Empirical Proxy	Hypothesized effect on likelihood of adoption
Resource-Based Factors: Rationalism	Population served – Size & type	• Size of service area population • LHD located in suburban or rural area (reference = urban)	↑ ↓
	Population served – Resources	• Log per capita expenditures (log $/pop.)	↑
	Public health activities & services offered	• Number of clinical services offered in 2005	↑
	Community partnerships	• Number of clinical services contracted • Area-level number of FQHCs per capita (#/ 1,000,000 persons)	↑ ↔
	Population served – Needs	• LHD located in health professional shortage area • Area-level percent of population eligible for Medicaid • Area-level unemployment rate	↓ ↓ ↓
Institutional Factors: Mimetic or Normative Isomorphism	Professional norms – Leadership interconnectedness	• LHD director: Clinician vs. non-clinician • LHD director: Position is full-time	↑ ↑
	Professional norms – Governance	• Board of Health • State governance	↑ ↓
	Regulatory pressures – Acquisition authority	• Control over IT purchasing (LHD/Internal, External, Shared)	↓

Table A2: Conceptual Model Specification for Research Aim 2

Organizational Theory	Theoretical Variable	Empirical Proxy	Hypothesized effect on likelihood of adoption
Resource-Based Factors: Rationalism	Population served – Size & type	• LHD change in jurisdiction between 2005 and 2010 • % change in size of service area population	↔ ↑
	Population served – Resources	• % change in log per capita expenditures ($/pop.)	↑
	Public health activities & services offered	• Change in number of clinical services offered 2005-2010	↑
	Community partnerships	• Change in number of clinical services contracted • Change in area-level number of FQHCs per capita (#/ 1,000,000 persons)	↑ ↓
	Population served – Needs	• Change in area-level percent of population eligible for Medicaid • Change in area-level unemployment rate	↓ ↓
Institutional Factors: Mimetic or Normative Isomorphism	Professional norms – Leadership interconnectedness	• Change in LHD director	↔
	Regulatory pressures – Attentiveness to legitimacy	• Plans to seek accreditation (self-reported, 2010 only)	↑

Table A6: Comparison of EHR Respondent LHDs versus non-EHR respondent LHDs (2005, 2010, and both years)

		2005		2010		2005 & 2010 +	
	LHD or Area-Level Characteristic+	**EHR Sample (n=407)**	**Others (n=1,893)**	**EHR Sample (n=514)**	**Others (n=1,593)**	**EHR Sample (n=106)**	**Others (n=1,734)**
Resource-based factors	Mean size of population served	209,426	114,102 **	108,793	210,508	138,843	231,712 **
	LHDs serving:						
	Urban	52.3%	37.7%**	47.1%	32.3%	54.7%	40.0%*
	Suburban	17.2%	20.5%	18.7%	17.1%	15.1%	20.6%
	Rural	30.5%	41.8%	34.2%	33.0%	30.2%	39.3%
	Mean per capita expenditures	$33.44	$30.68	$34.03	$33.38	$34.84	$33.45
	Mean number of clinical services offered	14.00	12.50 **	12.90	12.30	14.80	13.40**
	Mean number of clinical services contracted to other entities	0.90	0.90	1.60	1.30	0.90	0.80
	Mean LHD service area FQHCs per 1,000,000 population	1.4	2.1 *	2.4	2.7	1.3	2.1 *
	Percent LHDs serving HPSA	69.5%	70.7%	83.1%	82.4%	76.4%	75.1%
	Mean LHD service area percent population Medicaid eligible	20.0%	19.3%	19.6%	19.7%	18.9%	16.7%
	Mean LHD service area unemployment	5.1%	5.2%	9.2%	9.0%	5.0%	5.2%
Institutional factors	Executive director has clinical background	53.8%	50.2%	46.5%	43.0%	56.6%	46.9%*
	LHD executive director is full-time position	88.2%	84.2%**	92.8%	90.1%**	89.6%	88.6%
	LHD is governed by local board of health	74.2%	74.3%	72.8%	75.6%	73.6%	76.0%
	State-level governance	23.1%	21.9%	26.1%	26.9%	27.4%	22.0%
	LHD controls IT hardware purchasing decisions	25.1%	29.2%*	N/A	N/A	26.4%	29.7%

+ Values shown correspond to NACCHO Profile data for earliest year available in dataset

Significance levels for intra-year comparisons:

* $p < .1$ ** $p < .05$

Table A7 Comparison of Logistic Regression Models for LHD EHR Use using model specifications

	LHD or Area-Level Characteristic	**Original**	**Model Specification:** Removing Potential Outliers	**LHDs providing ≥ 1 service**	**LHDs providing ≥ 5 services**
Resource-based factors	LHD size of population served (standardized)	0.98	1.00	0.96	0.98
	LHDs serving:				
	Urban	*(Ref.)*	*(Ref.)*	*(Ref.)*	*(Ref.)*
	Suburban	0.96	0.88	0.84	0.81
	Rural	0.36***	0.40***	0.38***	0.38***
	LHD per capita expenditures (standardized)	1.12	1.10	1.13	1.14
	Clinical Services				
	Number of clinical services offered	1.16**	1.16**	1.15**	1.15**
	Number of clinical services contracted to others	0.97	0.96	0.96	0.83
	Communicable diseases factor	0.44***	0.43***	0.42***	0.39***
	Chronic condition screening factor	0.86	0.86	0.86	0.92
	Obstetrics factor	0.81	0.81	0.82	0.81
	LHD service area				
	Poverty index factor	1.02	1.08	1.09	1.07
Institutional factors	Executive director has clinical background	1.20	1.28	1.25	1.21
	LHD executive director is full-time position	0.92	1.14	1.19	1.36
	LHD is governed by local board of health	0.90	0.91	0.93	0.81
	State-level governance	1.03	0.91	0.94	0.92
	LHD controls IT hardware purchasing decisions	0.87	0.88	0.91	0.97

* p < .1
** p < .05
*** p < .01

Table A8: Sensitivity Analyses for Logistic Regression Models for Analytic Subsamples

	LHD or Area-Level Characteristic	Model Specification:				
		Original	Remove Possible Outliers	LHDs providing ≥ 1 service	LHDs providing ≥ 5 services	LHDs providing primary care or dental services
Resource -based factors	LHD size of population served (standardized)	0.98	0.98	0.98	0.99	1.39
	LHDs serving:					
	Urban	*(Ref.)*	*(Ref.)*	*(Ref.)*	*(Ref.)*	*(Ref.)*
	Suburban	0.96	0.99	0.98	0.95	0.93
	Rural	0.36***	0.37***	0.37***	0.32***	0.23*
	LHD per capita expenditures (standardized)	1.12	1.12	1.13	1.14	1.60**
	Clinical Services					
	Number of clinical services offered	1.16**	1.15**	1.14**	1.12*	1.03
	Number of clinical services contracted to others	0.97	0.97	0.98	0.86	0.84
	Communicable diseases factor	0.44***	0.46**	0.46**	0.45***	0.99
	Chronic condition screening factor	0.86	0.87	0.87	0.92	1.35
	Obstetrics factor	0.81	0.82	0.83	0.84	1.18
	LHD service area					
	Poverty index factor	1.02	1.03	1.03	1.06	0.94
Institu-tional factors	Executive director has clinical background	1.20	1.23	1.21	1.26	1.80
	LHD executive director is full-time position	0.92	0.91	0.94	0.80	0.24
	LHD is governed by local board of health	0.90	0.92	0.94	0.85	2.86
	State-level governance	1.03	1.05	1.07	1.03	1.20
	LHD controls IT hardware purchasing decisions	0.87	0.86	0.87	0.93	1.04

* p < .1
** p < .05
*** p < .01

Table A9: Comparison of Logistic Regression Models for LHD EHR Use using alternative outcome variable specifications

	LHD or Area-Level Characteristic	**Model Specification:** Original Model (Use = Implemented *only*)	Alternative Specification (Use = Implemented & Implementing)
Resource-based factors	LHD size of population served (standardized)	0.98	1.02
	LHDs serving:		
	Urban	(*Ref.*)	(*Ref.*)
	Suburban	0.96	0.69
	Rural	0.36***	0.57*
	LHD per capita expenditures (standardized)	1.12	0.88
	Clinical Services		
	Number of clinical services offered	1.16**	1.25***
	Number of clinical services contracted to others	0.97	0.96
	Communicable diseases factor	0.44***	0.51**
	Chronic condition screening factor	0.86	0.70**
	Obstetrics factor	0.81	0.80*
	LHD service area		
	Poverty index factor	1.02	0.81*
Institutional factors	LHD executive director has clinical background	1.20	0.72
	LHD executive director is part-time position	0.92	0.70
	LHD is governed by local board of health	0.90	0.46*
	State-level governance of LHD	1.03	1.55
	LHD controls IT hardware purchasing decisions	0.87	1.20

* p < .1
** p < .05
*** p < .01

Table A10: Sensitivity analysis for logistic models using alternative predictor and outcome variable years

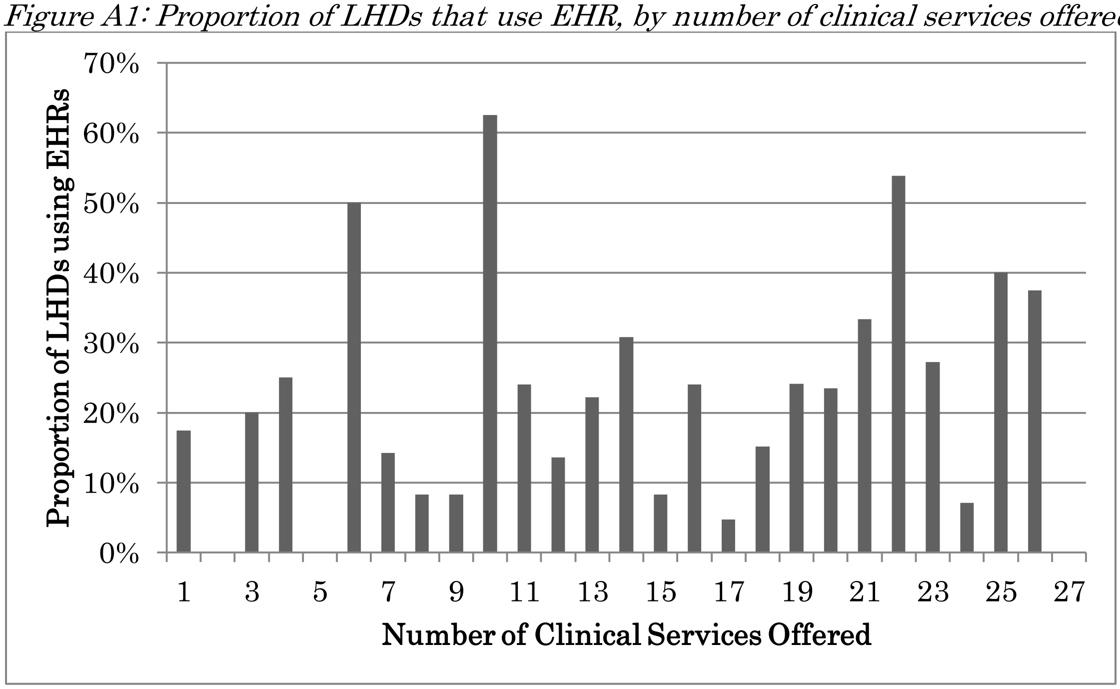
	LHD or Area-Level Characteristic	Model Specification: EHR Use: 2005 Predictors: 2005	EHR Use: 2010 Predictors: 2005	EHR Use: 2010 Predictors: 2010
Resource-based factors	LHD size of population served (standardized)	1.25	0.98	0.95
	LHDs serving:			
	Urban	*(Ref.)*	*(Ref.)*	*(Ref.)*
	Suburban	2.07**	0.96	1.13
	Rural	1.73*	0.36***	0.46**
	LHD per capita expenditures (standardized)	1.30*	1.12	1.27*
	Clinical Services:			
	Number of clinical services offered	0.96	1.16**	1.12*
	Number of clinical services contracted to others	1.03	0.97	0.89*
	Communicable diseases factor	0.95	0.44***	0.53**
	Chronic condition screening factor	1.14	0.86	0.84
	Obstetrics factor	1.04	0.81	0.89
	LHD service area:			
	Poverty index factor	0.94	1.02	0.9
Institutional factors	LHD executive director has clinical background	0.99	1.20	1.43
	LHD executive director is part-time position	0.61	0.92	1.15
	LHD is governed by local board of health	1.43	0.90	0.65
	State-level governance of LHD	1.29	1.03	0.53*
	LHD controls IT hardware purchasing decisions+	0.78	0.87	
	LHD plans to seek accreditation+			1.52

+ Variables not ascertained in both 2005 and 2010.
*   p < .1   ** p < .05   *** p < .01

Table A11: Service provision patterns for communicable disease factor services

	Number of communicable disease services offered							
	0	1	2	3	4	5	6	7
Number of LHDs	125	31	46	30	33	48	131	68
Proportion Using EHR	16%	39%	24%	13%	24%	25%	21%	18%
Total number of services offered	0.8	7.8	9.4	12.3	13.7	14.5	16.3	20.1
Proportion of LHDs Offering:								
Tb Screening	0%	84%	100%	77%	85%	98%	99%	100%
Tb Treatment	0%	6%	87%	73%	58%	90%	99%	100%
Family Planning	0%	10%	4%	43%	55%	48%	86%	100%
HIV Screening	0%	0%	9%	53%	73%	75%	99%	100%
STD Screening	0%	0%	0%	30%	85%	98%	100%	100%
STD Treatment	0%	0%	0%	17%	42%	83%	100%	100%
HIV Treatment	0%	0%	0%	7%	3%	8%	16%	100%

Figure A1: Proportion of LHDs that use EHR, by number of clinical services offered



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Chapter IV:

Use of Health Information Exchanges in Underserved Settings:

Two Local Initiatives in Small Physician Practices & Health Centers

Abstract

Health information exchange (HIE) is an important tool for improving efficiency and quality and is required for providers to meet Meaningful Use certification. However widespread adoption and use of HIE has been difficult to achieve, especially in settings such as smaller-sized physician practices and federally qualified health centers (FQHCs). We assess electronic data exchange activities and identify barriers and facilitators to HIE participation in two underserved settings.

We conducted key-informant interviews with stakeholders at 14 practices and clinics. Interviews were recorded, transcribed, and then coded in two waves: first using an open-coding approach and, after refining the study's codebook based on the first wave of coding, a second wave of selective coding to identify themes that emerged across interviews.

We identified barriers to HIE use at three levels—regional (e.g., existence of other area-level exchanges; number, type, and size of partner organizations), inter-organizational (e.g., strong relationships with exchange partners; achieving a critical mass of users), and intra-organizational (e.g., type of electronic medical record used; integration into organization's workflow). A major facilitator of HIE use was the improved care-coordination clinicians could provide to patients as a direct result of the information available through the HIE. Utilization and perceived benefit of the exchange systems differed based on several practice- and clinic-level factors.

Small physician practices and FQHCs appear to share common challenges in implementing and using HIE. We also found evidence suggesting that the successful adoption, implementation, and use of an electronic data exchange was influenced by factors at multiple levels within the healthcare system. Some of these factors are likely not modifiable by individual health care organizations, though it is still relevant for system

administrators and users to consider their impact on proposed or existing systems. Others may in fact be modifiable and therefore may be priority areas for consideration in adoption or usage reviews. Nevertheless, the limited availability of solutions to overcome these barriers currently presents a major challenge to the broad and effective use of HIE.

Introduction

Reflecting the importance of health information technology (health IT) to the future of American healthcare (Institute of Medicine 2001), the 2009 HI-TECH Act made available more than $30 billion to encourage hospitals and clinicians to make "meaningful use" of information technology (Blumenthal and Tavenner 2010).

To qualify for these incentive payments, healthcare providers must, among other things, be able to exchange patient healthcare information electronically between providers and across clinics (Adler-Milstein, Bates et al. 2009), a capacity that many believe will help address both cost and quality concerns (D'Aunno, Vaughn et al. 1999; Walker, Pan et al. 2005; Vest, Zhao et al. 2011; Institute of Medicine 2012). Initial data suggest that these predictions may be borne out, with some settings reporting some reductions in costs and improvements in quality (eHealth Initiative 2008; Magnus, Herwehe et al. 2012; Shade, Chakravarty et al. 2012).

There are two ways in which this exchange might be undertaken. One, a health information exchange (HIE) consists of the technology and governance that enable exchange of data between multiple stakeholders. The second, a regional health information exchange organization (RHIO) is an organization that provides an HIE to stakeholders in a specific region to enable exchange of a broad range of patient data housed in multiple organizations. (Wager, Lee et al. 2009)

Currently, use of HIE in the U.S. lags, with approximately 20% or less of U.S. hospitals having an HIE in place prior to the HI-TECH Act (Vest 2010). RHIOs face an even steeper challenge, requiring multi-stakeholder buy-in across numerous organizations. As a result, many RHIOs are underperforming or failing altogether (Frohlich, Karp et al. 2007; Adler-Milstein, Bates et al. 2009).

While the number of HIEs in operation grows, concerns remain about finding sustainable business models and funding sources. Adoption (the positive decision to participate in the HIE and undertaking of concrete steps to ensure its feasibility) and use (regularly accessing HIE data from external sources and, if applicable, actively sharing one's own data) of HIEs participation remains relatively low (eHealth Initiative 2008).

Perhaps more concerning than low overall levels of use is evidence of differential adoption and use of HIE across provider types and care settings (Jha, DesRoches et al. 2009; Bishop, Press et al. 2013). Involvement of small- and medium-sized ambulatory practices has lagged relative to hospitals and large ambulatory settings (Ross, Schilling et al. 2010). This disparity is especially important given that small ambulatory settings serve a disproportionate number of traditionally-underserved individuals (Bach, Pham et al. 2004). Other sources of care for the underserved such as Federally Qualified Health Centers (FQHCs) face these same problems (Shields, Shin et al. 2007).

HIE in Small Primary Care Practices

Very little is known about the specific facilitators and barriers of HIE adoption and use by smaller-sized ambulatory care practices. The only published study conducted in this target population represents findings from nine small primary-care practice organizations and was performed prior to the 2009 HI-TECH Act (Ross, Schilling et al. 2010). The study identified potential hypotheses for why HIE has not spread widely, but also focused heavily on process mapping and workflow management. No subsequent research has confirmed its findings, nor has research been conducted to extend this line of inquiry to other health care delivery settings, or to examine this issue since the incentive-altering HI-TECH Act reimbursement changes were instituted. Such research is needed to develop and test a strategic framework for effectively disseminating HIE based on more recent knowledge about facilitators and barriers to the spread of HIE.

HIE at Federally Qualified Health Centers

FQHCs are a critical part of the American healthcare safety net, providing primary health care for millions in high-need communities (Hurley, Felland et al. 2007). Almost all FQHCs operate under heavy financial constraints (McAlearney 2002), making health IT acquisition and HIE adoption especially difficult. Ironically, the FQHC setting is one example of the type of provider that could benefit the most from having shared access to a client's complete health record and the accompanying gains in quality. While no recent estimates are available for the prevalence of HIE in FQHCs, estimates of FQHC adoption of electronic medical records (a necessary precursor for HIE) lagged considerably relative to larger practices and hospitals (Shields, Shin et al. 2007). This study seeks to bring to light the needs, opportunities, and challenges with respect to HIE at FQHCs.

Research Aims

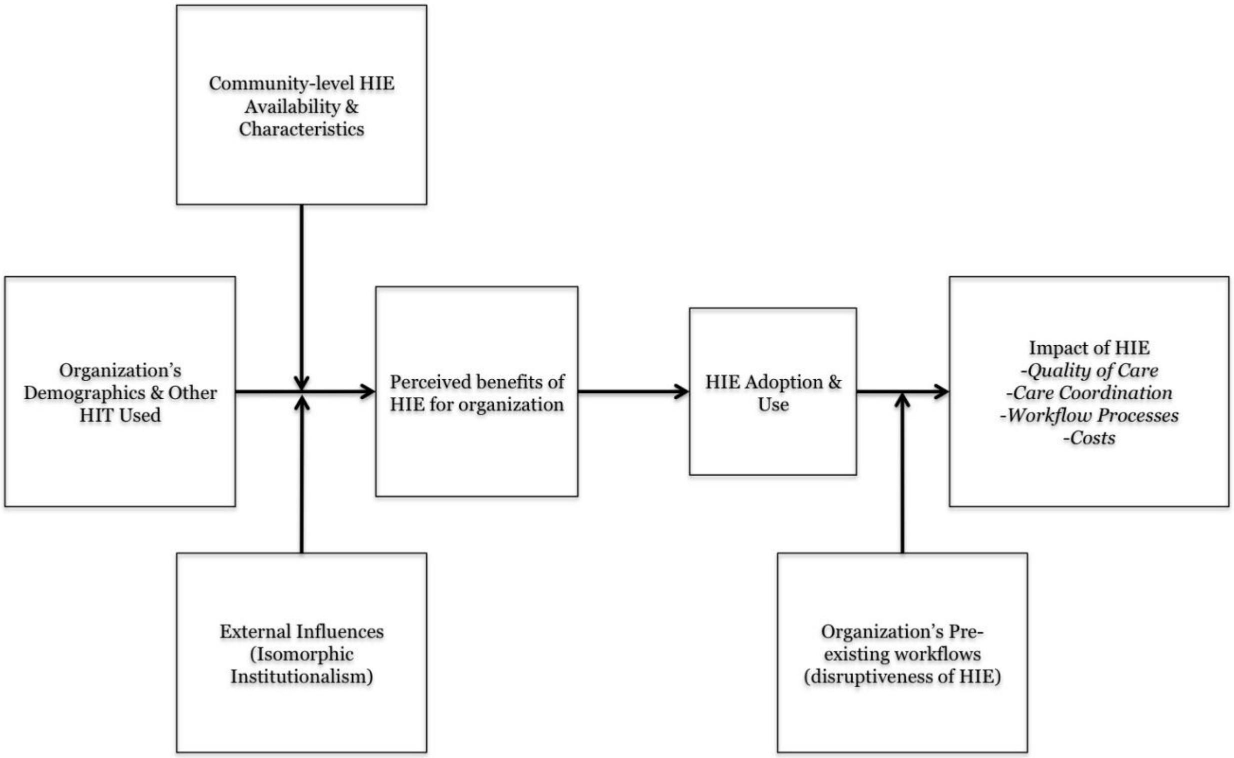
This purpose of this study is to generate knowledge about facilitators and barriers to the spread of HIE in underserved populations. To this end, we identified two community partners: Citrus Valley Health Partners (CVHP), a provider network leading a HIE effort in the East San Gabriel Valley, an underserved health care market in the Greater Los Angeles Area, and West Side Community Health Services (WSCHS), the largest FQHC in Minnesota and an active participant in a ten-member consortium of FQHCs in the Minneapolis-St. Paul metropolitan area. The aim of this study is to conduct key informant interviews with community collaborators to generate hypotheses regarding facilitators and barriers to the spread of HIE in smaller-sized primary care practices FQHCs.

Conceptual Framework

Through this study of physicians, practice managers, information technology specialists, and other stakeholders at community partner organizations, we sought to understand the motivations and challenges faced by smaller-sized practices and FQHCs to adoption and use of HIE. We aimed to identify factors influencing individual HIE readiness for change, provider motivation to better plan and coordinate care, and/or the potential for improved population health. We also examined the organizational barriers in using HIE.

We developed a logic model to shape development of the initial key-informant interview guides used in data collection. The model is shown below in Figure 1. We hypothesized that the availability and characteristics of existing HIE efforts, organizational demographics and patients served, and normative external influences would all impact a practice's or clinic's perceived utility of HIE. This, in turn, would influence their adoption. Subsequent use of the system may then lead to an impact in terms of quality, care coordination, or costs. Impacts may be moderated by the extent that the HIE use disrupts preexisting organizational workflows.

Figure 8: Logic model of barriers and facilitators to HIE adoption within target population



Methods

This study included primary data collection at two community partner organizations. Citrus Valley Health Partners (CVHP) is a provider network in East San Gabriel Valley, California. CVHP includes three hospital campuses and nearly 1,000 providers. The network provides care for many traditionally underserved individuals, serving predominantly Hispanic communities, with over 40% of care going to underinsured and uninsured individuals.

CVHP providers operate independently at small or solo practices and are free to select and acquire the health IT products suitable to their practice. Technical support is available through CVHP administration as is financial support tied to certain centralized initiatives. One such undertaking was a roll-out of the Citrus Health Information Exchange (CHIE), a system that shares information among CVHP-affiliated hospitals and providers, and with laboratories and others in the community. CHIE participation requires use of certain EMR vendors, but enables providers to view and edit patient records in real time. Since not all providers want to or are able to use CHIE-compatible EMRs, an additional web-based system called *Collaborate* was installed to enable all providers to view CHIE data and to securely message other providers. To date provider engagement and progress in clinician use of the system as intended has been variable. Little is known about what motivates *Collaborate* users or what barriers exist for non-users.

The second group of partner organizations came from the Federally Qualified Health Center Urban Health Network (FUHN) in the Minneapolis-St. Paul metropolitan area in Minnesota. FUHN is a consortium for ten FQHCs that recently partnered with the Minnesota Department of Human Services to operate an Accountable Care Organization for Medicaid patients as a component of Minnesota's Medicaid Health Care Delivery System demonstration project. FUHN is governed by the CEOs or executive directors of each of the ten FQHCs comprising this safety-net ACO and shares an administrative service contract among all 10 organizations.

FUHN has recently undertaken a data exchange initiative known as *CentraHealth*, aimed at improving each FQHC's access to electronic exchange with hospitals relevant to its ACO patients. The system is still being formally established and very little is known about organizational facilitators and barriers to participation in this exchange effort.

Data Collection

Data was collected for this study through semi-structured key-informant interviews (DiCicco-Bloom and Crabtree 2006) and qualitative data analysis (Ash and Guappone 2007). We develop separate guides for interviews with physician practices and with FQHCs guided by organizational behavior and socio-technical theories.

An iterative review and comment process was used with contacts at CVHP and FUHN to pilot test the interview guide and ensure face validity. The study used a community-based participatory research approach, so we also modified the interview guide to include coverage of topics of interest and benefit to both partner organizations.

Recruitment of Study Participants

Study participants were purposefully selected at both community partners. We sought to interview individuals who would be involved in the adoption and integration decisions at each organization, so we targeted the physicians at the small-sized practices and administrators at FUHN clinics.

At smaller-sized practices, we targeted providers who were more- and less-frequently using the system to elicit ideas and opinions from both groups. We enrolled three of the four practices involved in pilot-testing the system. We also enrolled five of the remaining practices that were not involved in the initial pilot-testing and who had lower levels of system use as of September 2013. *Collaborate* usage status and practice contact information was provided by CVHP administrative partners.

At FUHN, we successfully enrolled five FQHC practices. We purposefully sought practices with and without Epic EMR systems as this distinction was identified in initial meetings as a fundamental distinction in current HIE access and capabilities given the high usage of Epic EMR in the Minneapolis-St. Paul market.

Interview Data

We conducted interviews with a total of 16 providers, office managers, and clinic administrators in 13 practices and clinics. 15 of the 16 interviews were conducted in person. 11 of 13 practices agreed to have interviews digitally recorded. Field notes were taken for the remaining two and typed immediately following completion of the interviews. One interview was conducted via phone and was also digitally recorded. All recordings were professionally transcribed and spot-checked for accuracy.

Each of the interviews lasted 20 – 60 minutes (median = 32 minutes), for a total of more than 350 minutes of recorded interviews plus four sets of field notes from non-recorded interviews.

While the relevant issues for each setting had substantial overlap, separate interview guides were developed for the two office settings in our study. The interview guides allowed the discussion to be largely guided by the interviewee, but ensured consistent inclusion of relevant topics across all interviews. Guides were refined based on input from each community partner organization prior to use in the field. Participants were given a $25 gift card for participation in the study.

Data Analysis

A two-part approach was used to code all interview data. First, each interview transcript was coded using an open-ended coding approach. This grounded portion of the analysis allowed theories to emerge from the data rather than be forced into a conscribed set of categories (Creswell 2013). Next, the data were analyzed again to identify themes from the open-coding approach and from our logic model. Similar approaches have been used in several other qualitative studies of health IT or HIE (Ross, Schilling et al. 2010; Unertl, Johnson et al. 2012; Friedman, Crosson et al. 2013). Interview transcripts were analyzed using Atlas.ti version 7.1.

Results

Summary characteristics of the 16 interviewees and their work locations are summarized below in Table 1 (small-practices) and Table 2 (FQHCs). Our interviews included a mix of *Collaborate* pilot practices and non-pilot practices, primary care/family practice and specialists, younger and older physicians, and practices that had and had not yet fully transitioned to EMR. We were also successful in recruiting FQHCs of varying size and both EMR users and non-users.

Table 1: Summary characteristics for small-size practice interviews

Practice Code	Practice Specialty	Interviewee	Provider Characteristics: Speaks non-English language(s)	Provider Characteristics: Years in Practice	Practice Characteristics: # Physicians	Practice Characteristics: # administrative FTEs	Practice Characteristics: Transitioned from paper to EMR	Practice Characteristics: Involved in *Collaborate* pilot
A	Family Medicine	Office Manager	Yes	> 30	1	3	No	Yes
B	Obstetrics	Physician	Yes	10 – 20	1	2	Yes	Yes
C	Family Medicine	• Physician • Physician	Yes Yes	< 10 < 10	2	3	Yes	No
D	General Surgery	Physician	No	> 30	1	2	Yes	No
E	Internal Medicine	• Physician • Office Manager	Yes	> 30	1	3	No	No
F	Internal Medicine	Office Manager	No	20 – 30	2	2	No	Yes
G	Family Medicine	Physician	No	20 – 30	1	2	Yes	No
H	Pediatrics	Physician	Yes	< 10	1	3	Yes	No

Table 2: Summary characteristics for FQHC interviews

Clinic Code	Interviewee(s)	Annual visits	EMR System
1	Chief Executive Officer	> 30,000	Centricity
2	Chief Executive Officer	> 30,000	Epic
3	• Executive Director • Information Manager	10,000 – 20,000	SuccessEHS
4	Executive Director	10,000 – 20,000	*Adopting* Epic
5	Executive Director	20,000 – 30,000	Centricity

Collaborate System Findings

A table outlining the full set of barriers and facilitators identified through coding of interview transcripts is shown in the Appendix (see Table A1 and Table A2, respectively).

Nearly all interviewees expressed positive sentiments about the system in the abstract. Timeliness of information was among the most frequently cited benefits, as was the attractive user-interface. One of the most frequently discussed ways in which *Collaborate* impacted these eight practices was in terms of workflow. We found numerous instances in which the system both improved and hindered practice workflow. Practices A and E, neither of which had completed the transition from paper to electronic medical records, both noted added work from the system due to having to print out information separately for each patient through additional clicking, then manually add the information to the patient charts. Neither indicated any sort of permanent re-working of processes as a result of *Collaborate* system use. Other practices that had completed the transition from paper to electronic records noted improvements in workflow: " [With *Collaborate*] *I can go to that one location, download it or if I know the patient's coming to see me I can even review before the patient even gets here and that saves time*."

While one of the major purposes of the *Collaborate* system was to provide an additional avenue for physician-to-physician communication, only a single user—a physician involved in piloting the system —mentioned that the messaging function was one of the most useful features of the system. Others noted1) having technical difficulties ("*Some of my messages got over with attachments [e.g., images or visit notes]. Some of her messages came back to me answering my messages or she sent me a message brand new. But it wasn't a hundred percent.*"), 2) not having a sufficient base of active users to message with ("*My use of Collaborate is very limited and the reason is that I'm a specialist, so I have* *to wait until there are enough primary care physicians who are online who may refer me a patient or who we may have a mutual patient.*") and, 3) subsequently not using the system enough to find it useful ("*I was struggling with the messaging. So then I hadn't looked at it for a while… I couldn't even remember my password. I went back in and looked at it and it's still fun. The bells and whistles are fun to play with. I no longer can message, though.*")

One of the most commonly cited barriers to *Collaborate* use by office managers was incomplete patient information. Several noted that it was sometimes easier, or at least more reliable, to access this information via an existing hospital-based system enabling electronic access to hospital records:

> *When clinic is especially busy, even if I had [both hospital-based and Collaborate systems] already pulled up on two screens, I would just go where I was more confident I could find the patient. With the [hospital-based system] I can be closer to 100% confident that I'll find the patient there. Even if it's harder to use or the information isn't quite as good. I just don't want to risk not finding the patient.*

Interviews with physicians did not reveal similar barriers to retrieving complete information on patients. Instead, several physicians expressed a preference for *Collaborate*'s layout and ability to access patient information compared to their EMR:

> *When I launch into my EMR I'm in one specific patient. When I launch into Collaborate I see my patient list so I can see everything that's happened on a patient of mine within a certain timeframe and then, individually, launch from Collaborate into each patient to see what has changed, what's the delta from the last visit?*

Physicians did not note, even after direct prompting, that patients had particularly strong concerns about *Collaborate*. Where concerns did exist, physicians found them to be easily allayed by discussing or demonstrating the finite range of data available through the system. We did, however, note concerns from multiple regarding data, ownership, and liability issues: "I *put in data on my patients but who else sees that data? What are my* *legal responsibilities regarding that data? I think that was probably my only reservation about [Collaborate].”*

To summarize the findings discussed above, we aggregated the barriers we identified into groups operating at three levels within the healthcare system, as shown below in Table 3.

Table 3: Levels of Barriers to Successful HIE Implementation or Use

Level	**Barrier**
Regional	- Existence of area-level exchanges - Regional market characteristics, including number, type, and size of partner organizations
Inter-Organizational	- Relationships or previous experiences with exchange partners - Need to achieve a critical mass of users
Intra-Organizational	- Health IT used (e.g., type of EMR used & integration into organization’s workflow) - Data ownership and provider liability

In addition to these barriers to the use of *Collaborate*, we also identified several facilitators and benefits commonly reported by physicians and less commonly reported by office managers.

Four of the most commonly cited benefits of HIE use pertain to the care that physicians could provide to patients as a direct result of the information available through *Collaborate*. Exemplar quotes from three physicians are highlighted below in Table 4 to suggest four potential avenues for added value to the patient.

Table 4: Four potential avenues for added value to the patient through HIE & exemplar quotes

Initial-visit productivity	"When I get the information from the hospital or other providers, there is more value for the patient. I can know more even for the first visit. And usually can get more accomplished during that first visit than if I have to repeat all of the info that's already in the system from somewhere else."
Completeness of patient records	"A lot of time patients come to see me and they'll say I have X, Y, Z and I'll say well, did you have an ultrasound? They say, yep, I had it two weeks ago, but maybe the primary care hasn't sent it to me. Then, either the patient has to bring it or we have to call and that sort of thing. So I think it's smoother by the fact that all that's in one location. I can go to that one location, download it or if I know the patient is coming to see me, I can even review before the patient even gets here and that saves time. I think it allows me to focus more of my time listening to the patient's concerns and answering her questions rather than searching for data."
Avoidance of duplicative tests (and financial risks)	"During the initial visit, you can see if they had the labs done. You won't duplicate any labs that were recently done and the patient wouldn't have to pay out-of-pocket if you repeated those tests or x-rays. Also, it's just better care. Let's say you had a condition where you really needed to get that lab, I just think it's better care."
Improved non-visit consults	"I had a patient with lung cancer who called me at two in the morning because he was anxious. He was having shortness of breath. He couldn't breathe correctly. I was able to actually use [HIE] data from his previous encounters in the hospital and his other providers. I saw what his actual oxygen saturation was and it was actually in the normal range, so I just told them maybe you better just go ahead and call the 911 and the ambulance. He actually ended up in the ICU, intubated and things like that, because of his lung condition."

One physician took these value-added areas a step further, suggesting that *Collaborate*, or similar systems, might serve as a quality signal for the physician in terms of attracting or retaining patients, encouraging referrals from other physicians, and of the medical group itself:

> *I like that idea that CVHP was on the cutting edge of doing this being aware of the fact that we all have to do it. I think a plus for me was that my hospital was out front setting up an HIE, facilitating a process where physicians can get an EMR and connect to the hospital, even though I didn't get the hospital's EMR, I got my own. Another way it benefits me, I think, as a specialist, I think few of us have the system so I think that impresses the primary care physicians that if they have a choice of two general surgeons to send to who are equal in every*

> *other way, one has the system, the other one doesn't, I think the primary care doc's going to send to the general surgeon that has it, assuming that the primary care doc does.*

Another physician noted that she relies on the system to make her aware of when her patients are being seen at the nearby hospital, enabling her to drop by if she is already in the building. She believed this benefits both her and the patient:

> *That fosters the relationship and helps build it, so it's not like she's this isolated person that multiple doctors are taking care of and we're disconnected. It gives a connect. She may not know how I know that she's there, but she cares and she likes the fact that I know that she's there.*

No physicians reported making substantial changes to their practice workflow as a result of using *Collaborate*. Likewise, no physicians reported substantial cost savings for their practices as a direct result of system usage, though nearly all felt that, at some level, there was savings as a result of using the system:

> *Right now there's lots of discussion but just because you're speaking to someone that feels like, yeah, this is a great benefit, he's got to convey that to the higher ups who have to have that same sense. When it comes down to half a million dollars, or I have no idea I'm just throwing that number out, but to upgrade the equipment for the connectivity, where's the return on investment? You can't really quantify that for somebody.*

As opposed to physicians, office managers tended to express very positive overall sentiments about the system, including its design and interface, but offered little concrete information about ways in which *Collaborate* had facilitated cost-savings or improved patient care, care coordination, or office workflow.

CentraHealth System Findings

Compared to the *Collaborate* system, which had been fully implemented at the time of our interviews, the *CentraHealth* system was in the planning and pre-implementation phase at the time of the interviews. Each practice was therefore able to offer views on the system as they saw it impacting their own work and ability to access information from external sources.

There was near unanimity in each practice's data exchange needs—especially as they related to the Accountable Care Organization patients each organization is responsible for under the FUHN. They also shared an understanding of current challenges facing FQHCs with respect to external electronic exchange of data. Minneapolis-St. Paul is without a regional health information exchange organization, so electronic exchange efforts are generally established on an "as needed" basis between organizations with shared data needs and shared incentives for establishing and maintaining the interface.

The use of the "as needed" approach to HIE in the community ended up being a substantial barrier for FQHC stakeholders interviewed. All organizations reported serving high proportions of uninsured patients that receive care from a limited number of hospitals, though their share of total patients at any given hospital was low. Consequently, each FQHC had stronger incentives to set up data exchange linkages with a hospital than any given hospital did: *"It just comes down to priorities. We're so far down the priority list for [the hospital organization] to even contemplate doing a direct interface with [FQHC] that it's time commitment prohibitive, and cost prohibitive for them."*

Another area that was discussed as both a barrier and facilitator to HIE use was the high prevalence of Epic EMR use by hospitals and health systems in the Minneapolis-St. Paul market. One FQHC used Epic and specifically noted that they only recently adopted

Epic specifically because they wanted to be able to be compatible with systems at nearby hospitals. They noted that, while the acquisition, implementation, and maintenance costs for the system were high, they believed that in the long-run, having easier potential for "tie-ins" to electronic data exchange with other health care delivery organizations would make the investment worthwhile. Another FQHC was in the process of changing to Epic from another non-Epic EMR system. They noted widespread dissatisfaction with their previous EMR as a major catalyst for the change ("*I've been told about three times in the last two years by two medical directors here. 'You're going to lose your employees if you don't get this system fixed.'"*) rather than a strategic shift towards greater interoperability with external organizations. One of these organizations even went as far as to suggest that funds and effort currently geared towards the *CentraHealth* data exchange should be redeployed towards shifting other FQHCs onto Epic.

The FQHC interview participants who did not have Epic or have plans to adopt it unanimously agreed that not having it was a substantial barrier to electronic data exchange: "*There is no direct interoperability with the hospital systems here in the metro area. If you want to play in that world, you have to be Epic. So if you're outside the Epic bubble, you're not able to exchange information*." The ten FUHN organizations were thus relatively united on their data exchange needs and their understanding of the barriers they faced ("*We are unsure how important it is for the FQs to share information back and forth. We think it's a heck of a lot more critical that the individual FUHN clinics can share information with hospitals and the specialists that they use.*"), but they were split over how best to address these needs.

The current solution, known as *CentraHealth*, was specifically designed to combat one of the biggest issues to FUHN's ACO model—the lack of hospitals in the ACO network.

One FQHC saw *CentraHealth* as the best way to leverage their collective bargaining power to get the data they want:

> *That's a potential game changer for us. It will allow us to say, okay, hospital X, Y, and Z, who are all Epic, you guys develop one interface for CentraHealth and it will push the information down to us. We'll actually go ahead and help pay for that plug-in, and then you're plugging into one interface instead of five interfaces. Things like that to make it easier by having one central data repository.*

Such an undertaking by a group of ten FQHCs requires a high level of cooperation. While FUHN engagement levels appeared to vary between organizations, nearly all interviewees expressed feelings that relationships among the ten FUHN members had become more collegial over time:

> *In the beginning of time… the FQs were pretty fiercely competitive and very parochial in their business dealings and didn't want to share any information and that type of thing. That environment has almost completely transformed into one of, instead of looking for reasons not to work together, we're looking for reasons to work together… FUHN is a successor of that and I think probably was brought about in large measure because of the efforts around the combined EMR and practice management.*

Interview participants identified the importance of three major factors in fostering this cooperative spirit. First was the formal FQHC ACO arrangement shared among the organizations. Interviewees noted having very similar responsibilities, incentives, and barriers to operating part of their organizations as ACOs. Second was the strong and continued partnership they had with their administrative services partner (a large health services organization in the region). Every interviewee expressed some level of trust in the partnership, usually referring to the organization by name rather than the names of individuals who work within that organization: "*I really trust [them] and I trust they know what to do and they've had good results in other states. So I don't feel like we need to second guess all of their approaches except when it's going to come to our clinic maybe we have to look at jeopardizing our system somehow*." Third was the role of individuals within

FUHN. Interviewees all mentioned one individual as important to the coalition, to its vision and initiatives, and to spearheading projects such as *CentraHealth* and also mentioned that some organizations were more involved than others. While none of the interviewees listed the actual FQHCs they felt were more or less engaged in leading the coalition, multiple interviews included statements that indicated there was some agreement about who those organizations were:

> Clinic E: *FUHN is, obviously, bigger than three or four organizations, but those three organizations play a pretty important role in FUHN right now so I think we can take a little credit for it.*
>
> Clinic D: *Well, there are people who were in the original group that did all the contracting with the state and they seem to have a better handle on everything that's going on and that's quite fine with me because I concentrate on my stuff.*

Opinions about *CentraHealth* itself were divided. There was a relatively even split between Epic users and non-Epic users. While each respected the system's ability to simplify and reduce the number of interfaces required to connect 10 FQHCs to multiple hospitals throughout the region, non-Epic users saw substantial potential value in the system. These organizations tended to view it as a potential solution to many of the barriers to HIE discussed above and were overall quite positive about *CentraHealth* and how it might impact their clinic and the care they provide:

> *[CentraHealth] is going to be the repository and the data base to… receive and organize relevant clinical and claim information from a whole variety of sources, multiple sources and can organize it in such a way so that all of the data from all of those sources can be reported out and summarized on a patient-specific basis… It's going to be used to identify high-risk patients, high-utilizing patients and help direct our intervention strategies to where we think we can make the most improvements.*

In comparison, one Epic-user expressed substantial doubts about the system. This organization was less focused on the data exchange opportunities, which may have been relatively less important given the preexisting potential for Epic-to-Epic exchange, and more focused on the system's potential impact on clinic workflow:

> *We're not going to be automatically say we're going with CentraHealth… My concern is I'm not willing to try to customize our systems in order to accommodate CentraHealth. The other concern was how efficient is it to have two systems right next to each other? Our doctors don't have time to do that. Our Medical Assistants don't have time to do that.*

Discussion

In both settings examined in this study, physicians, office managers, and clinic administrators expressed strong support for improved ability to electronically exchange information and reliably access that information. Several themes from the study's logic model were consistently reported across physician practices and FQHCs.

First, the lack of community-level HIE availability drove physician practices and FQHCs to develop custom solutions to address data needs. Neither group reported having sufficient leverage to gain access to all of the data they needed and came up with the best solution possible given realities on the ground. We selected these two organizations for this study for precisely this reason; our goal was to examine unique solutions developed in the field to assess barriers and facilitators to their successes.

Second, external influences were relevant and important in both settings. The number, size, and type of partners were all important factors in determining HIE adoption and use. In the smaller-sized practices, several interviewees mentioned the "Catch-22" of not having enough other providers regularly accessing and checking the system and therefore not finding the system useful enough to use themselves. While many individuals mentioned the importance of medical group expectations and training received, there were almost no mentions of other peers who encouraged or promoted system use. In FQHCs studied, their close and pre-existing ties are the reasons why the *CentraHealth* system was developed in the first place. The group's administrative service partner and one FUHN clinic administrator were frequently mentioned as a system champions, underscoring the strength of leadership required for a home-grown HIE. Moreover, the *CentraHealth* exchange was motivated by the shift towards ACOs and system-level accountability, with every organization mentioning this as a substantial motivating factor. In short, without external influences—both positive and negative—the systems would likely look far different than they currently do.

Third, the practices' and FQHCs' use of other health IT was central to adoption and usage decisions in almost every interview. Smaller-sized practices in which physicians had completed the transition away from reliance on paper records expressed a broader range of perceived benefits of the exchange system than practices that still relied on paper records. We hypothesized that this may be due to the types of information being sought by front-end or support staff versus physician HIE users. Staff might seek information to add to the patient's chart, while physicians might have a more open-ended need for the information (Vest, Zhao et al. 2011; Unertl, Johnson et al. 2012). Both of these groups indicated that they do not always make full use of the system, supporting previous findings that providers do not commonly utilize existing HIE data (Vest 2009; Vest, Zhao et al. 2011).

We had originally hypothesized that these other IT systems used within an organization would impact the perceived benefits of HIE. While we found this to be the case for the FQHC participants, we found little evidence that expectations of system effectiveness varied by their use of health IT and integration into workflow. Rather, incorporation of EMR into a practice's workflow moderated the usefulness of the system in smaller-sized practices. The practice of printing out patient charts and HIE data before patient encounters limited the range of interaction with the HIE system. The paper-based workflow represents an avoidable, but deliberately chosen, workaround that has become routinized over time (Friedman, Crosson et al. 2013). It is likely that paper-based workarounds limit the impact of HIE systems by clinicians and staff, and to other practices as well given that fewer physicians are then regularly accessing the system and thus able to communicate with one another.

We found that challenges related to obtaining a complete suite of data were viewed not only as data challenges, but also as technical challenges. In both settings, the difficulty and expense of getting additional interfaces set up was noted. Physician respondents spoke more commonly of the difficulties in getting such a link established ("*If we could get [Hospital A] data that would be great, but I don't know how we would do that*"), while FQHC administrators generally spoke of this more as a technical issue ("*This is an Epic town*"). Importantly, none of the interview participants discussed limited HIE use as a financial issue that might be solved with additional spending.

As has been seen in other iterations of electronic exchanges, the perceived and actual benefits of electronic exchange did not accrue to a single set of constituents. Both providers and FQHC administrators underscored the benefits of HIE use for patients, front office staff, clinicians, clinics or practices, and for payers. In both cases, however, funding for the exchanges came mainly from a single source (clinics or practices), underscoring the challenge of finding sustainable funding sources to support ongoing exchange efforts (Adler-Milstein, McAfee et al. 2008).

Limitations

We collected primary data from those providers and clinics who are actively involved in the adoption or use of the exchange efforts examined. The participant sample may differ from smaller-sized practices or FQHCs who do not adopt electronic data exchanges (e.g., physicians that have not yet transitioned from paper records, or clinics not located within a network of other FQHCs that might enable a system similar to *CentraHealth*). Our sample was small, although it was purposefully selected. Interviews were conducted in two separate geographic locations (California and Minnesota); experiences in other areas may differ. This is an especially important limitation to note given that one level of barriers we identified operated at the regional level. In areas with different market and EMR vendor characteristics a different set of factors may emerge.

The two HIEs studied were also in different lifecycle phases. *Collaborate* has already been formally adopted by and rolled-out to providers at CVHP and is currently being used by providers. *CentraHealth* is still being considered for adoption by FUHN organizations and is not yet being used by providers. As such, the barriers and facilitators identified in each setting may be specific to the respective adoption and use phases when interviews were conducted.

It is unclear how broadly the findings generalize to other settings because of the limited research on HIE use, though our study was aimed at generating hypotheses to clarify the limited use of HIE in underserved settings. We wanted to interview a range of users and non-users of the HIE systems, but it is possible that individuals who declined to be interviewed may have experienced different barriers or facilitators to use of the systems. Additional perspectives may thus broaden our findings rather than confirm or reject our conclusions. To date, analysis of qualitative data have been analyzed by one individual.

Further work on this topic will likely include additional investigators' open coding of transcripts, application of codes to a subset of interviews, and resolution of potential coding differences.

Conclusion

We found important facilitators and barriers to electronic data exchange in smaller-sized practices and FQHCs. In each setting, we examined an exchange initiative tailored to suit local needs and found evidence that adoption and use of the systems differed according to factors at three levels.

First, regional-level characteristics played an important part in determining the type of data exchange possible (e.g., through a RHIO or not, number/ size/ type of partner organizations) and determining the practicality of exchanging data between organizations (e.g., in markets dominated by a given health system). Second, inter-organizational factors such as the presence of close and trust-filled relationships with exchange partners and achieving a critical mass of users. Third, intra-organizational factors such as the type(s) of health IT used within an organization (e.g., EMR brand or adaptation of workflow to fully leverage IT capabilities) was linked to whether and how the exchange system was used. These broad factors might facilitate the development of measures of the readiness of a region, a coalition, or an organization to participate in electronic data exchange, even in the absence of local federally-sponsored exchange programs, e.g., RHIOs.

Understanding barriers and facilitators to HIE adoption and use can aid individuals, organizations, and networks in their HIE adoption and use decisions. Future studies should clarify the relative importance of factors at regional, intra-organizational, and inter-organizational levels in facilitating health information exchange. Limited solutions to overcome these barriers currently presents a major challenges to the broad and effective use of HIE.

<u>Supplementary Material</u>

<u>Key Informant Interview Guide for Smaller-Sized Physician Practice Interviews</u>

Facilitators & Barriers to Use of HIE
in Smaller-Sized Practices
Key Informant Interview Guide – *Collaborate* Users

(1) Conceptualization of HIE

As you know, this interview will be about health information exchange. To begin the interview, what does "health information exchange" mean to you?

(2) Practice decision-making

We will have a few questions about your practice's decision-making structure.

- Can you please talk a bit about who is ultimately responsible for making decisions about:
    - how the practice is run on a day-to-day basis?
    - acquisitions or technology upgrades?
- Who else is involved in these types of decisions? What is their role?

(3) Current use of Health IT

- Describe how your practice currently records and stores patient records. Does your practice use an electronic medical records system?
    - If EMR = yes:
        - What EMR system do you use?
        - How long have you had your current system?
        - Overall, how satisfied with the system are you?
        - What are your favorite features of the system?
        - What are your least favorite features?
    - If EMR = no:
        - Have you ever considered or investigated an EMR system for this practice?
        - If so, what were some of the reasons you chose not to acquire an EMR at this practice?
- Besides EMR, what are some of the major technological systems that your practice uses or has plans to use?

(4) Current electronic and non-electronic exchange of clinical information

Next, we will ask a few questions about your current access to and use of HIE.

- Do you currently have access to Collaborate at this practice location?
- Have you had access to any type of HIE at previous places of employment?
    - If yes, how would you compare them with what you currently have?

(5) Motivators, barriers, and incentives for adoption of Collaborate

- [*If has HIE*]: Thinking specifically about your practice, talk about the major reasons why you ultimately decided to participate in Collaborate.
    - If you were around at the time or have talked about it with others:
        - what were some of the biggest motivating factors for initially deciding to participate?
            - Were there any specific benefits envisioned?
        - what were some of the biggest issues or sticking points that had to be worked out before you began participating?
            - Were there any specific problems envisioned?
        - do you recall any specific incentives that were helpful in securing your participation?
            - Any particularly influential system features or functions?
            - Any particularly influential leaders, advocates, or system champions? (Can be either within or outside of the medical group)
    - For your practice today,
        - what are some of the biggest benefits you think Collaborate brings to your practice?
        - what have been the most useful features?
            - Clinical documentation
            - Labs
            - Patient demographics
            - Referral management
            - (One that doesn't exist)
        - are there any drawbacks to HIE in your practice?
- [*If doesn't have HIE*]:
    - Do you know of any existing HIE efforts at CVHP or in the community?
        - If so, have you ever considered participating in it?
        - [*If mentions Collaborate*]: Talk about the most major reasons why you do not participate in Collaborate.
    - Hypothetically, what sort of benefits do you think participating in a HIE could offer your practice, if any?
    - Hypothetically, what sort of drawbacks or downsides do you think there might be to HIE participation?

(6) Community partnerships

In order for Collaborate to be effective, it requires participation from other partners. Next we will discuss some of the partners in your community and how they are or might be integrated into Collaborate.

- What types of organizations does your practice interact with regularly?

    - [*Want to get enough info to be able to broadly categorize, don't need names, contacts, etc.*]
- Thinking specifically about Collaborate, what organizations would be the most helpful to include in the information exchange? Why?
- Have you had any trouble or push-back trying to get these organizations to participate in information exchange?
    - Have you been able to overcome these issues with any partners? How?

(7) Patient considerations

Next, we'd like to ask some brief questions about how you perceive Collaborate impacting the care your patients receive.

- What do you believe are the most major benefits to the patient that flow from your use of Collaborate?
- Do all of your patients benefit equally from Collaborate?
    - If not, what type(s) of patients benefit the most?
- Are there any specific types of patients who you feel are not realizing the benefits?
    - Spanish or other non-English speakers?
    - Those without medical homes?
- Other vulnerable or underserved patient populations?

Key Informant Interview Guide for Federally Qualified Health Center Interviews

Facilitators & Barriers to Use of HIE
in Federally Qualified Health Centers
Key Informant Interview Guide – *CentraHealth* Users

(1) Current use of Health IT

- Describe how your clinic currently records and stores patient records. Does your clinic use an electronic medical records system?
  - *If EMR = yes:*
    - What EMR system do you use?
    - How long have you had your current system?
    - Overall, how satisfied with the system are you?
    - What are your favorite features of the system?
    - What are your least favorite features?
  - *If EMR = no:*
    - Have you ever considered or investigated an EMR system for this clinic?
    - If so, what were some of the reasons you chose not to acquire an EMR at this clinic?
- Besides EMR, what are some of the major technological systems that your clinic uses or has plans to use?

(2) Current electronic exchange of clinical information

Next, we will ask a few questions about your current access to and use of health information exchange, or "HIE".

- Do you currently have any HIE underway at your clinic location?
- Have you had access to any type of HIE at previous places of employment?
  - If yes, please talk a bit about how that compares to what you currently have.
- [*If doesn't have HIE*]:
  - Do you know of any existing HIE efforts in your clinic or in the community?
    - [*If yes*]: have you ever considered participating in it?
      - [*If yes*]: What factors played into your decision not to participate?

(3) Motivators, barriers, and incentives for adoption of HIE

- [*If has HIE*]: *See questions at end of document. Not anticipating clinics to have HIE at this time, but questions have been prepared just in case*
- [*If doesn't have HIE*]:
  - What do you think are some of the biggest barriers to you participating in a HIE?

            - (*Want to be sure to address barriers external and internal to the organization, if applicable*)
    - Have you identified or thought about any potential solutions to these barriers?
    - Hypothetically, if you could get an HIE set up:
        - what sort of benefits do you think participating in a HIE could offer your clinic, if any?
        - Hypothetically, what sort of drawbacks or downsides do you think there might be to HIE participation?

(4) CentraHealth Interface

- Are you aware of the "CentraHealth" initiative?
- [*If no*]: *skip to next section*
- [*If yes*]:
    - What is your role in the project?
        - What is your organization's role in the project?
    - What do you know about how the effort got started?
        - Whose idea was it?
        - Any major players or organizations that you feel were especially important to getting the ball rolling?
        - Were there other ideas for similar initiatives that were also considered?
        - How does this effort compare to previous efforts at information exchange for FQHCs in the metro area?
            - *(Especially interested in learning about concrete take-aways from previous efforts such as MNHIE*)
    - What sort of benefits do you anticipate seeing as the effort gets up and running?
        - Are there any anticipated drawbacks?
    - What are some of the biggest barriers you see to getting this up and running?
        - (*Want to be sure to address barriers external and internal to the organization, if applicable*)
        - Have you identified or thought about any potential solutions to these barriers?
    - In your opinion is this effort something unique to this Twin Cities-based FQHC and hospital network? Or is this something that could work in other cities or with other types of organizations?
        - Are there any keys to success that you've seen? Anything or anybody that was absolutely crucial to have?

(5) Community partnerships

In order for HIE to be effective, it requires participation from other partners. Next we will discuss some of the partners in your community and how they are or might be integrated into the HIE efforts here.

- What types of organizations does your clinic interact with regularly?
  - [*Want to get enough info to be able to broadly categorize, don't need names, contacts, etc.*]
- *[If HIE = no]* what organizations do you think would be important to involve in a future HIE?
  - Have you ever engaged or discussed potential HIE with these organizations?
    - [*If yes*]: Were both organizations receptive to adopting HIE? What were some of the issues that arose in those talks?

(6) Clinic decision-making

Next, we have a few questions about your clinic's decision-making structure.

- Can you please talk a bit about who is ultimately responsible for making decisions about acquisitions or technology upgrades?
- Who else is involved in these types of decisions? What is their role?

(7) Patient considerations

Finally, we'd like to ask some brief questions about how you perceive HIE impacting the care your patients receive.

- Very briefly, can you talk about the patient population that you serve?
  - [*Want to get very general info—race/ethnicity, insurance, languages spoken, etc.*]
- What do you believe are the most major benefits to the patient that flow from your use of HIE?
- Do all of your patients benefit equally from HIE?
  - If not, what type(s) of patients benefit the most?
  - Are there any specific types of patients who you feel are not realizing the benefits?
    - (*E.g., language barriers, underserved or other vulnerable patient populations?*)
- What, if any, drawbacks do you anticipate for patients as a result of HIE?

(8) Wrap Up

Those are all the questions I had prepared for today. Are there any other issues or topics that we did not discuss or areas you'd like to talk more about?

[*If no*]: Thank you very much for your time. We very much appreciate your contributions to this project. As a small token of our appreciation we have a $25 Starbucks gift card to thank you for your time and input.

If Clinic has HIE, include these topics in the conversation:

Motivators, barriers, and incentives for adoption of HIE

- Thinking specifically about your clinic, talk about the major reasons why you ultimately decided to participate in HIE.
    - What were some of the biggest motivating factors for initially deciding to participate?
        - Were there any specific benefits envisioned?
    - What were some of the biggest issues or sticking points that had to be worked out before you began participating?
        - Were there any specific problems envisioned?
    - Do you recall any specific incentives that were helpful in securing your participation?
        - Any particularly influential system features or functions?
        - Any particularly influential leaders, advocates, or system champions? (Can be either within or outside of the clinic)
- For your clinic today,
    - what are some of the biggest benefits you think HIE brings to your clinic?
    - what have been the most useful features?
        - Clinical documentation, Labs, Patient demographics, Referral management, (Others)?
    - are there any drawbacks to HIE in your clinic?

Community Partnerships

- What other organizations are involved in your current HIE?
    - Do they all participate equally?
    - Do you think that the data that each organization provides is equally helpful? Or are there organizations whose participation is more helpful than others?
- Are there other organizations that would be helpful to include in the information exchange? Why?
    - Have you had any trouble or push-back trying to get these organizations to participate in HIE?
    - Have you been able to overcome these issues with any partners? How?

Table A1: Barriers for Electronic Exchange of Health Information

Description	Example Quotations
Patient privacy concerns (perceived)	So for example, I have some patients who will come in and they will see my computer and they go, oh, you're computerized, too, and there's almost sometimes a sense of negativity. I had a doctor tell me their patient was looking at their stocks while they weren't in there because they just left it on but, of course, it wasn't on other patients. But the email section was on and the Internet was on and it was a particular stock while they're waiting for their doctor do their own business. But I've also heard horror stories where other patients were able access other patients while they were in the office because they leave that port on. They just forgot to turn it off after they did the vitals, et cetera.
Patient privacy concerns (reality)	Actually, some of my patients prefer that because they prefer that the doctors already know that what their problem is because they assume that when they go to the doctor all their records are there and so when they move to another clinic you automatically get all the records, but that doesn't always happen. So if I have a patient who has a negative approach, oh, god you're on the computer, too, what I do is I show them the HIE. I will launch into the HIE and the scenario that I say is if you presented to an emergency room today and could give no information to the doctor taking care of you let me show you the information that he has as opposed to what you think he's going to have. He's going to know that you have thyroid disease, that you have ulcer disease. He's going to know that you have allergies to sulfide. He's going to know that your current medications are omeprazole and Synthroid. That's really all he's going to know. So they think that everything in my record is being sent out there and I'm trying to show them it's really just the critical information that you would want them to have if you couldn't give it to them So this is what I show patients when they're here and they have a question. I say, look, it's really your allergies. It's that you saw me but nothing about it. It's your problems. It's your medications. When they see that they're, okay, that's like nothing. So they're okay with that.
Insufficient information/ Uncertainty avoidance	My use of Collaborate is very limited and the reason is that I'm a specialist. I'm a surgical specialist, so I have to wait until there are enough primary care physicians who are online who may refer me a patient or who we may have a mutual patient. We love Collaborate. It's easy to work and navigate. It's pretty, it's in color. But we don't use it. We can't access all the patients like you can via Citrix.

	When clinic is especially busy, even if I had both Citrix and Collaborate already pulled up on two screens, I would just go where I was more confident I could find the patient.
Insufficient training & follow-up	I would like to see someone stop by and say just checking in and see how your Collaborate is going. Any questions? Because we sort of feel like a little abandoned out here. We've got it set in but it's sort of stuck. It's not really moving so we've got this big system that's there, but it hasn't gotten to the point of being a practical everyday use type level… Maybe they need a newsletter, Collaborate newsletter, where they put FYI information that would come out quarterly or monthly that would keep Collaborate alive, if you will, as we wait for more and more primary care doctors to get into the system. I think that would be helpful, just educational stuff, a frequently asked questions type thing, something like that. But I would say having more patients in the system will allow me to use the system better, but also having strong support that just sort of checks in, maybe support/education type thing would be a benefit, too. Because I may learn how to do it one time but if I don't do it every day, I'm going to forget that. I've got to start all over again.
Competing tech priorities	The hospital dictates that we have to learn this and that. Now they want me to learn CPOE. So first I have to get the hospital system training and get that up and running. Then I can do the systems for my practice here.
Difficulty messaging between providers	But the accessory parts of the Collaborate that were kind of fun is collect the data and organize the data. It allowed you to look at inpatient/outpatient stuff quite nicely, but I was struggling with the messaging. So then I hadn't looked at it for a while then… I couldn't even remember my password. I went back in and looked at it and it's still fun. The bells and whistles are fun to play with. I no longer can message, though.
Added steps in workflow	My program doesn't connect directly with the hospital program. I jump on the website to Citrix then Meditech and just pull out all my patient data.
Technical reliability issues	So some of my messages got over with attachments. Some of her messages came back to me answering my messages or she sent me a message brand new. But it wasn't a hundred percent.
Not real-time communication	My feeling was that Collaborate was designed to send information back and forth to the doctors. It doesn't have to be instantaneous so you're not making a patient an immediate appointment for that patient, right? So you don't have to be online with their office in real time. It's supposed to be there and then at the end of the day doctors can look at their dashboard, oh, I got a message from so and so. I should check it. Dr. so and so sent me a message. I think that was the purpose of Collaborate to update you, inform you, et cetera. It doesn't have to be done in real time.

Table A2: Facilitators for Electronic Exchange of Health Information

Description	Example Quotations
Timeliness of care	It allows you not to delay care because you have access to that information so I think that moving towards a Health Information Exchange is a good idea.
Facilitate better decisions about patient care	During the initial visit you can see if they had the labs done. You won't duplicate any labs that were recently done and the patient wouldn't have to pay out of pocket if you did repeat those tests or x-rays and, also, it's just better care. Let's say you had a condition where you really did need to get that lab, I just think it's a whole better care. I had a patient with lung cancer who they called me at two in the morning because he was anxious. He was having shortness of breath. He couldn't breathe correctly. So I was able to actually use data from his previous encounters in the hospital and his other providers and see what his actual oxygen saturation was and it was actually in the normal range so I just told them maybe you better just go ahead and call the 911 and the ambulance. He actually ended up in the ICU, intubated and things like that, because of his lung condition. So I think it is helpful to have that access instantaneously and remotely wherever you are and it's important. It helps you take better care of your patients because you know exactly what has already been done and what they need.
Signal of quality	I like that idea that Citrus Valley was on the cutting edge of doing this being aware of the fact that we all have to do it. So I think a plus for me was that my hospital was out front setting up an HIE, facilitating a process where physicians can get an EMR and connect to the hospital, even though I didn't get the hospital's EMR, I got my own. Another way it benefits me, I think, as a specialist, I think few of us have the system so I think that impresses the primary care physicians that if they have a choice of two general surgeons to send to who are equal in every other way, one has an EMR, the other one doesn't, I think the primary care doc's going to send to the general surgeon that has the EMR, assuming that the primary care doc does. So when that doc's going to decide who to refer to, with everything else being equal, he likes getting my reports back when I've seen the patient. He likes the fact that I can print out education material and give it to the patient immediately. So I think there's an opportunity to benefit there, also. I can't quantify it financially, but I think t is a benefit.
Updates on patients currently in hospital	So I can open up Collaborate and see there's a patient of mine that's in the hospital right now. Now, I may not be involved in that care but that doesn't mean if I go over for lunch at the hospital I might stop on the floor and say hi. There's nothing that's more

	rewarding to the patient to know that somebody cares and, oh, you stopped by to see me.
Coordination of care	That fosters the relationship and helps build it so it's not like she's this isolated person that multiple doctors are taking care of and we're disconnected. It gives a connect. She may not know how I know that she's there but she cares and she likes the fact that I know that she's there.
Improved timeliness of information & streamlined workflow	I think that's definitely beneficial to the patients. A lot of time patients come to see me and they'll say I have X, Y, Z and I'll say well, did you have an ultrasound. They say, yep, I had it two weeks ago but maybe the primary care hasn't sent it to me. Then, either the patient has to bring it or we have to call and that sort of thing. So I think it's smoother by the fact that all that's at one location. I can go to that one location, download it or if I know the patient's coming to see me I can even review before the patient even gets here and that saves time. I think it allows me to focus more of my time listening to the patient's concerns and answering her questions than searching for data and all that sort of thing.
Technological flexibility	Now the shift is toward Collaborate, which is where most of us are because there's so many different EHR's out there. We aren't all using the same system. So Collaborate, then, becomes more practical for a 700-member medical staff, group or body which makes sense. A lot of us were trying to make an argument from the very beginning that Collaborate just makes more sense unless everybody's going to have the same EMR and chances are that's not going to happen unless all the physicians are employees or something like that.
First-visit Productivity	When I get the information from the hospital or other providers, there is more value for the patient. I can know more even for the first visit. And usually can get more accomplished during that first visit than if I have to repeat all of the info that's already in the system from somewhere else.

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Chapter V:

Conclusion

The papers in this dissertation have focused on examining the adoption, use, and impacts of health IT in several important settings.

The first paper examined the impact of electronic warnings on the provision of evidence-based care for acute bronchitis and upper respiratory infection. More specifically, we estimated that the use of electronic warnings by clinicians was associated with approximately a 20% in the likelihood of patients receiving antibiotics. This estimate is important for two major reasons. First, serious and sustained efforts are underway to reduce the incidence of antibiotic prescriptions for non-indicated conditions such as acute bronchitis and upper respiratory infection. An innovation that can decrease antibiotic prescribing by 20% should be viewed as a major tool in the fight against overuse of antibiotics in the United States, though to date we have not observed a decline in the incidence of antibiotic prescribing for acute bronchitis or URI. Second, this estimate is one of the first national-level estimates of the effectiveness of health IT in changing practice in ambulatory care settings. It represents the first national-level look at the impact of electronic warnings on antibiotic prescribing practices. Many previous studies have focused on the impact of health IT in one setting, possibly because it was not previously feasible to generate national estimates when usage levels were still low.

The second paper's focus on patterns of LHD use of EHR over time is also notable and novel. Previous studies have not facilitated cross-year comparisons of EHR use in these settings, so it is not known whether EHRs are commonly used by LHDs and, if so, whether there are trends towards greater use over time. At best, adoption of EHR appears stagnant between 2005 and 2010. The relatively low levels of use we observed may signal a need for additional consideration of how EHRs can be tailored to meet the needs of local health departments to ensure they also receive the benefits projected to stem from the use of health IT.

The third paper focused on an area that has been shown to lag with respect to health IT, and especially HIE, use. We identified multiple levels of barriers to participation in current HIE efforts by smaller-sized physician practices and FQHCs—regional, inter-organizational, and intra-organizational. We also identified several ways in which HIE participation benefits practices and clinics, mostly pertaining to the ability to provide valuable consultation and care for patients. While some of these factors may be modifiable by health care organizations, limited solutions to overcome these barriers currently presents a major challenge to the broad and effective use of HIE.

This dissertation's three papers collectively address issues related to our understanding of where, how, and why health IT is being used. These questions are expected to be critical for the future health IT work that may seek to foster a deeper understanding of the interaction between individuals, organizations, and the IT systems themselves.

The findings might also help promote adoption of health IT among areas currently underrepresented, perhaps the next direction of adoption promotion efforts for an otherwise rapidly-adopting United States. The use of EHR by LHDs, for example, was shown to be relatively low compared to other settings. This dissertation was not able to assess why that may be the case. Determining ways to bolster the relevance and usefulness of EHRs for LHDs may be fruitful for the departments, their partners, the clients they serve, and for broader efforts to protect and promote the public's health.

After identifying potential barriers and facilitators to HIE participation by small physician practices and FQHCs, there may be particular value in developing measures of how these factors play into the adoption and successful use of HIE. Future work on an evidence-based and validated measure of Readiness for HIE is a likely next step for this line of inquiry.

There is ample opportunity for future research on health IT adoption and use issues for these settings that can help to ensure that the impact of these systems helps deliver on the promise of health IT for healthcare in the U.S.