Adoption of Healthcare Information Technology and the Impact on Clinician Behavior

by

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Abstract

It is widely believed that healthcare information technology (health IT) can improve care and lower costs. However, the pattern and uptake of beneficial features of health IT is poorly understood, and is an important part of realizing the full benefits of health IT. This thesis examines the factors relating to adoption and use of reporting features within an outpatient practice management system. A retrospective observational study was performed utilizing web log data from a practice management and electronic health record system vendor. Two years of data were analyzed on the use of features within the system in two different scenarios: the use of a newly released custom reporting feature among existing clients, and the use of a physician-level monthly report among new clients.

Among these two different populations and features, the first use and subsequent utilization exhibited similar patterns. Using the Bass model of technology diffusion to quantify the adoption of these features, it was found that adoption had a low social component (coefficient of imitation) and a high personal component (coefficient of innovation). One physician's use of a feature in his practice did not appear to influence whether a new physician joining the same practice would use the feature. In addition, the earliest users of a feature tended to utilize that feature more often. Practices and providers that used these features performed better across three of four operational and financial metrics.

The purchase and installation of a health IT system by an organization does not ensure that individuals within it will fully utilize the system and realize all the benefits. Incentives for health IT should focus on the advantages gained from these systems, and not merely on their purchase. Health IT vendors should be cognizant of the way they introduce new functionality to their clients in order to ensure maximal use.

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Statement of Purpose and Goals

Healthcare information technology (health IT) has been well studied in medical literature, yet these studies have produced a variety of conflicting answers and even more questions. There is a general consensus that health IT can produce cost savings and improve the quality of care, yet for any given technology there exist studies that show a negative impact. In addition, there are varying estimates of the level of adoption of health IT systems in the United States, depending on how "adoption" and the system being studied are defined.

Knowledge of health IT in an outpatient context is particularly lacking. Despite the fact that most physicians work in small ambulatory practices and deliver the majority of care, outpatient clinics have been particularly slow to adopt health IT. Due to this slow adoption and the de-centralized nature of this population, there are particular challenges in studying health IT in this group.

Despite these challenges, a growing number of people are looking to health IT to help save the U.S. healthcare system. This increased attention to health IT was underscored recently by the $19 billion invested in health IT by the Obama administration to encourage adoption of electronic health records (EHR) systems among inpatient and outpatient physicians. This increased installed base of EHRs, and of health IT generally, creates significant opportunity to capture the savings and improvements hinted at in the literature. However, it is only the first step. It is the effective use of the capabilities that these systems provide today and in the future that will lead to value being realized, not merely the installation of these systems. This fact is not being ignored by those who are guiding health policy. In a recent article in the New England Journal of Medicine, Dr. Blumenthal, the National Coordinator for Health Information Technology, stated, "…if EHRs are to catalyze quality improvement and cost control, physicians and hospitals will have to use them effectively."[1]

This study looks at a population of outpatient medical providers over a two year period of time and across different health IT components. It attempts to explore adoption and effective use in greater detail in order to answer the following questions:

- Is there a consistent pattern of health IT adoption across functionality?
- Are there factors that correlate with adoption of health IT?

- Is the effective use of health IT associated with cost savings or operational improvements?
- What can companies and regulators do to maximize health IT adoption so that the full range of benefits can be realized?

Introduction and Background

This study explores the dynamics of healthcare information technology adoption, with a particular focus on the implications for Electronic Health Records. The dynamics that come into play in an organization after a health IT system has been installed are critically important to realizing its benefits, yet are poorly understood. This pilot study is intended to show how the purchase and installation of a health IT system – the typical measures of health IT adoption – relate to the full utilization of the system.

The answer to this question has implications in a number of areas. Most directly, researchers in health IT adoption can use this pilot study to understand the dynamics of health IT adoption at a more fundamental level. However, the implications extend to physicians' practices, EHR companies and policy makers. Organizational factors can play a significant role in determining the success of IT, and practices that are unable to realize improvements will lose increasing amounts of revenue from pay-for-performance and government reporting initiatives. EHR vendors whose clients do not realize the full value of their investment will be at a competitive disadvantage in an increasingly competitive market. Finally, if policy makers hope to realize the cost savings that are possible from health IT adoption, they must understand the dynamics at play and create the appropriate incentives.

Significance of Health IT Adoption

Health IT adoption has become a significant issue due to the large amount of attention and investment in this area. With the recent American Recovery and Reinvestment Act (ARRA), the government is investing $19 billion to encourage the adoption of health IT, and $17 billion of that will be used for direct payments to doctors and hospitals for EHR adoption[2]. These incentives are intended to help achieve President Obama's goal of complete computerization of medical records by 2014[3]. Through this adoption, the Congressional Budget Office estimates that savings of $34 billion over 10 years could be realized through a reduction in medical errors and decreased healthcare utilization[4].

This investment also has significant implications for the EHR marketplace. The U.S. EHR market is currently estimated at around $1.2 billion dollars in terms of yearly revenue[5,6]. Therefore, the sizeable government investment in this area could effectively double the size of this industry in a five year period.

Reporting in Health IT

The ARRA recognizes the importance of effective utilization by specifying that providers must demonstrate "meaningful use of health information technology", and gives the following three general criteria for this: 1. Quality metric reporting; 2. Connection to exchange data; 3. Certified systems[7]. While these guidelines have yet to be defined specifically as of this writing, it is generally believed that quality reporting will involve the submission of quality and outcomes metrics.

Reporting is becoming an increasingly important part of health care, and this trend was underway before the quality reporting provision of the ARRA was announced. For example, the Health Plan Employer Data and Information Set (HEDIS) was initially developed in 1991, and comprised numerous process and quality measures. More recently, the Physician Quality Reporting Initiative (PQRI) was established legislatively in 2007, and offers incentive payments as part of Medicare reimbursement for quality reporting[8]. In addition, non-government pay-for-performance programs are making up an increasing share of healthcare payment programs[9].

Benefits of Health IT

Information technology (IT) investment has led to improvements in many industries across a number of dimensions, so it is not unreasonable to expect similar benefits in healthcare. IT investment has been found to improve productivity and lower costs in multiple industries, and two-thirds of the labor productivity improvement from 1990-2000 has been attributed to IT[10,11,12].

In healthcare, it is believed that a number of benefits will accrue from increased IT adoption, but the evidence has shown mixed results[13,14]. A review of randomized controlled trials by Bales et. al (1996) involving a variety of clinical information systems found that certain features were associated with operational improvements[15]. A more recent review of the medical literature on the impact of healthcare IT by Chaudry et. al (2006) had more mixed results[16]. This study looked at EHR and decision support systems, and found that there was quality improvement due to better guideline adherence and decreased medical errors. The study also found that there were some efficiency gains due to decreased utilization of care. However, the impact on operational efficiency was mixed. A limitation of this study was that a significant proportion (25%) of underlying studies took place at four institutions with internally developed systems, whereas most outpatient physicians will acquire commercially developed systems.

This year, a study by Amarasingham et. al (2009), studying a set of hospitals in Texas, found that a higher level of use of clinical information systems was associated with lower mortality rates and a lower cost per admission for the population of patients older than 50 years of age[17]. Another recent study on the Kaiser Permanente HealthConnect program, which provided an EHR across multiple care settings as well as secure patient-provider and intra-provider messaging, showed a 26% decrease in office visits[18].

Increased spending on health IT has been shown to be associated with increased financial returns in certain situations. A firm level analysis of integrated health delivery systems by Thouin et al. (2008) found that an increase in IT spending and IT outsourcing were associated with increased firm profitability[19].

Current State of Health IT

Information technology is being used more and more in healthcare, and incentives from payers are an important part of this growth, going beyond those for EHRs in the ARRA. For example, in January 2009 Medicare began providing an incentive to doctors for e-prescribing, and now approximately 70,000 physicians utilize this technology, representing 12% of all office-based physicians[20].

Despite gains in certain areas, the U.S. continues to lag behind the rest of the world. A study by the Commonwealth Fund in 2008 found that the Netherlands, New Zealand, the United Kingdom and Austria have all achieved greater than 75% use of EHRs, which is significantly higher than the level of use in the U.S[21]. Support from the U.S. government has also lagged other OECD countries by as much as a decade[22].

The true level of U.S. adoption of health IT and EHRs in particular has been difficult to gauge. Burt and Sisk (2005), examining data from 2001-2003 based on the National Ambulatory Medicare Care Survey (NAMCS) of office-based physicians, found that an average of 18% of physicians used an EHR[23]. By 2008, a survey by the National Center for Health Statistics found that 38% of physicians were using an EHR, although only 4% of those systems were considered fully functional[24].

Effective Use and Benefits of Health IT

The value of health IT is realized not just from the installation of new technology, but with the widespread use and adoption of that technology. Research has shown that installation alone is not good enough to impact healthcare; individual factors within the organization can lead to wide variations in the gains from technology[25]. Research has also shown that the biggest gains come not only from adoption of the technology, but in changes in behavior that best take advantage of this technology[26]. In healthcare, effective use has been shown to be significant in realizing the benefits of EHRs[27]

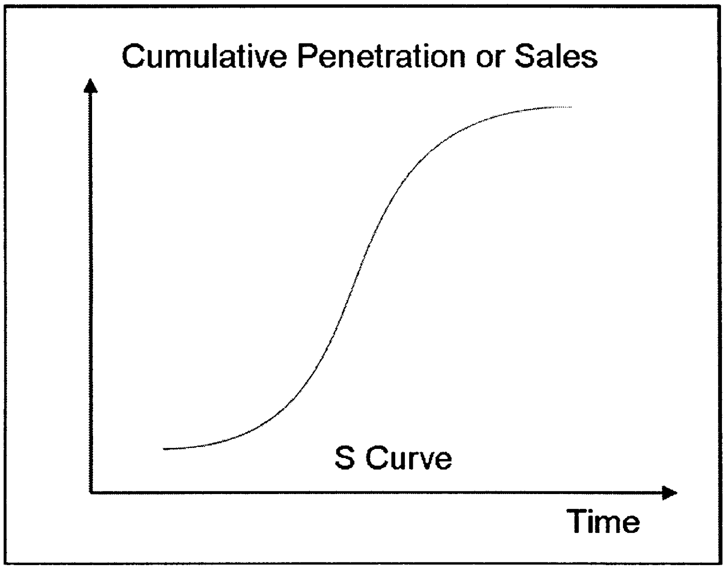
Davidson and Heineke (2007) describe five steps to realizing the full benefits of health IT[28]:

1. Availability of effective health IT systems
2. Installation of the system
3. Use of the system
4. Modification of work processes
5. Measurement of the effect on quality, efficiency and cost.

Technology Diffusion Model

The theoretical basis for the diffusion of new technologies was described in detail by Everett Rogers in *Diffusion of Innovations* in 1962[29]. He described how an intersection of social forces leads to the probability of adoption. Cumulative adoption, when plotted over time, results in the now-familiar S-Curve:

Figure 1. Cumulative Adoption S-Curve
Cumulative sales as a function of time[30]



In 1967, Frank Bass published *A New Product Growth for Model Consumer Durables,* describing formulas that could be used to model the growth in sales of new products based on the theories of Rogers. The Bass model has been utilized in healthcare to look at the adoption of durable goods, such as CT and MRI machines[31]. It has also been applied in health IT to predict the adoption of electronic health records by outpatient physicians, and develop recommendation for Informatics Nurse Specialist training[32,33].

Factors in Adoption of Health IT

Technology diffusion literature suggests that individual, technological and organizational characteristics influence the adoption and use of new technologies. Romano (1995) found that a combination of technological and organizational factors explained 52% of the variation in adoption of a computerized staffing system[34]. A 2005 study of outpatient practices in Massachusetts looked at organizational attributes associated with EHR adoption[35]. It found that larger practice size, hospital-based practices and practices that teach medical students were more likely to have an EHR. Another study, examining physician adoption of an ambulatory prescription expert system, found that 72% of physicians had significant use ($\geq$ 50% of prescription) after 6 months[36]. Burt and Sisk (2005) found that larger practices and certain specialties were more likely to have installed an EHR system[23]. Other factors, such as the physician's age and the payer mix were not found to correlate significantly.

Fischer, et. al. (2008) studied Massachusetts physicians' utilization of an e-prescribing tool[37]. This system was provided free of charge, and the population studied was mostly community physicians. They found that younger clinicians, pediatric practices and larger practices were associated with greater utilization of the system.

Background on athenaHealth

All data used in this study were provided by athenaHealth, Inc. athenaHealth is a Massachusetts-based provider of web-based practice management and EHR services and software. As of 2008, athenaHealth provided services to over 18,785 medical providers in 1,226 practices across 39 states[38].

athenaHealth releases new versions of its software at regular intervals, multiple times a year. Due to the nature of its software, all practices receive the new versions simultaneously. Each new version contains new functionality and feature changes. This regular and uniform update process combined with the rich data source due to the web-based software model created an ideal opportunity to observe how practices and medical providers adopted new features.

Methodology

Study Dataset

Identification of Features

Through discussions with athenaHealth, a set of features to be included in this study was identified. The criteria for inclusion were as follows:

- Available to a significant portion of the client base: the feature in question had to be available to a large enough population of individuals to produce statistically significant results.
- Provided at no additional cost: I aimed to remove cost as a factor of adoption.
- Optional to use: the client had to make a conscious effort to utilize the feature.
- The feature must provide actionable information: the feature had to provide information significant enough to the medical provider or practice such that it might initiate a change in operating or care procedures.

Through these discussions, the following features were identified:

- Report Builder – the report builder feature allows the client to create custom reports based on practice data on an ad-hoc basis.
- Clinician Performance Review (CPR) – the CPR is a monthly report that contains financial, administrative and operational metrics pertaining to an individual physician[39]. It is produced automatically for each medical provider in a practice three months after the practice "goes live" with athenaHealth (meaning that athenaHealth's software is installed at the client site, and they are ready to utilize the system).

Usage Dataset

For the features described above, athenaHealth provided a usage dataset. This dataset consisted of web log data for athenaHealth products covering the period January 1, 2007 to March 1, 2009. Since athenaHealth provides its software through a standard web browser via an internet connection, this dataset was sufficient to identify the utilization of the system. This dataset contained information on who accessed the feature, when it was accessed, and to what practice and department the user was logged in when the feature was accessed. The dataset excluded entries originating from athenaHealth employees and was limited to the features included in the study.

Demographic and Performance Dataset

In addition to web log information, athenaHealth provided de-identified information on the practices and medical providers using their services, including medical specialty, length of time as a client, geographic region of practice, and provider type. In addition, the following performance metrics were also available for each provider on a monthly basis:

- Days in Accounts Receivable (DAR) – measures how quickly claims were paid starting with the date that service was provided[40].
- Work RVUs per Month – measures the amount and complexity of work performed by the clinician. Work RVUs are not affected by insurance contracts, regional differences or unpaid claims.
- Denial Rate per Appointment – measures the number of denied claims given the number of patients seen by the provider.
- Hold Lag – measures the amount of time it took for the practice to resolve billing errors[41].

Collectively, these measures were used to assess the financial and operational performance of the providers and practices included in this study. One caveat to these metrics is that factors outside of a practice's control can influence their performance. DAR can be affected by how quickly the insurer processes claims. Denial rate can be affected by athenaHealth's performance in catching errors early on in the claim submission process as well as by insurers' rules. For the purposes of this study, I assumed that these factors affected each practice equally and on a uniform basis.

Data Classification

For the purposes of statistical analysis, certain data elements were categorized using standard classifications while ensuring a large enough population to achieve statistical significance. Table 1 and Table 2 show the categorizations performed.

Table 1. Provider Specialty Classification

Specialty Group	Specialties
Medical Specialty	Cardiology, Critical Care, Dermatology, Emergency Medicine, Endocrinology, Gastroenterology, Hematology, Immunology, Infectious Disease, Interventional Radiology, Medical Oncology, Nephrology, Neurology, Occupational Therapy, Ophthalmology, Optometry, Otolaryngology, Podiatry, Preventive Medicine, Psychiatry, Pulmonary Diseases, Rehabilitation Medicine, Rheumatology, Radiology, Urology
OB/GYN	Obstetrics and Gynecology
Other, N/A	Audiologist, Chiropractic, Certified Nurse Midwife, Nurse Practitioner, Pain Management, Physical Therapy, Psychology, Physician Assistant, Registered Dietician/Nutritionist, Unknown
Pediatric Medicine	Pediatric Medicine
Primary Care	Family Practice, General Practice, Geriatric Medicine, Internal Medicine
Surgical Specialty	Cardiac Surgery, Colorectal Surgery, General Surgery, Hand Surgery, Neurosurgery, Orthopedic Surgery, Plastic/Reconstructive Surgery., Surgical Oncology, Thoracic Surgery, Vascular Surgery

Table 2. Provider Type Classification

Provider Type Group	Provider Type
Doctor	Doctor of Chiropractic, Doctor of Osteopathy, Doctor of Podiatric Medicine, Medical Doctor, Optometrist, Clinical Psychologist (PHD), Resident
Mid-Level	Licensed Audiologist, Certified Nurse Midwife, Licensed Physical Therapist, Nurse Practitioner, Physician's Assistant
Staff	Medical Assistant, Registered Nurse, Technical Staff

Study Population

This study involved two different populations in order to understand adoption and use in two different scenarios (see Table 3 for all population characteristics). In the first scenario, I observed the way a new feature (Report Builder) was adopted by existing clients; in the second, I observed how new clients adopted existing functionality (CPR report).

Practices Included

To be included, a practice had to be a current client and not have given an indication that they would be terminating their contract with athenaHealth. The reason for this second requirement was that practices that have given notice that they are terminating their contract begin to utilize other systems, which then distorts the data collected by athenaHealth. "New practices" were defined as practices that went live with athenaHealth software on or after January 1st, 2007 and before October 1st, 2008. This ensured that there were data for the entire time the practice was in the study, and that there would be a minimum of six months of data. "Existing practices" were defined as practices that were athenaHealth clients as of January 1st, 2007, and were still clients as of March 1st, 2009.

Table 3. Provider Population Characteristics
Selected characteristics for the two populations used in this study. "Existing Practices" denotes those providers that were with practices that were clients as of January 1st, 2007, as well as study exclusions. "New Practices" denotes those providers with practices that became clients after January 1st, 2007, as well as study exclusions.

	Existing Practices		New Practices	
Value	**N**	**%**	**N**	**%**
Practice Size				
1-3	510	15%	474	15%
4-5	218	6%	197	6%
6-10	476	14%	397	12%
11-50	1,325	38%	953	30%
>50	974	28%	1,209	37%
Practice Specialty				
Primary Care	817	23%	893	28%
Pediatric Medicine	182	5%	63	2%
OB/GYN	314	9%	84	3%
Medical Specialty	647	18%	1,186	37%
Surgical Specialty	525	15%	451	14%
Multispecialty	1,018	29%	553	17%
Region				
Northeast	1,427	41%	607	19%
Midwest	651	19%	527	16%
South	1,037	30%	1,113	34%
West	388	11%	983	30%
Total	3,503	100%	3,230	100%

Statistical Analysis

Statistical analysis was performed using STATA version 10.1 and Microsoft Excel 2007. Multivariate linear and logistic regression with stepwise estimation using backwards selection was used with a $p<=0.05$ cutoff to test a variety of assumptions. Model variables are listed in each case.

To quantify and compare exploration curves, the Bass diffusion model was used[42]. This is represented by the following formula:

$$N_t = N_{t-1} + p(m - N_{t-1}) + q\left(\frac{N_{t-1}}{m}\right)(m - N_{t-1})$$

Equation 1. Technology Diffusion Model

where N_t = the number of adopters at time t, p = coefficient of external influence (innovation) representing the inherent willingness to adopt, q = coefficient of internal influence (imitation) representing the factor that social forces play in adoption, and m = the total market potential.

To determine the coefficient of innovation (p) and imitation (q), I used Excel's Solver functionality to create a linear optimization. Its objective function was to minimize the difference between the observed exploration curve and a technology diffusion curve described by p, q, and m for all monthly time points t.

Results

Provider Exploration and Use of the Clinician Performance Review

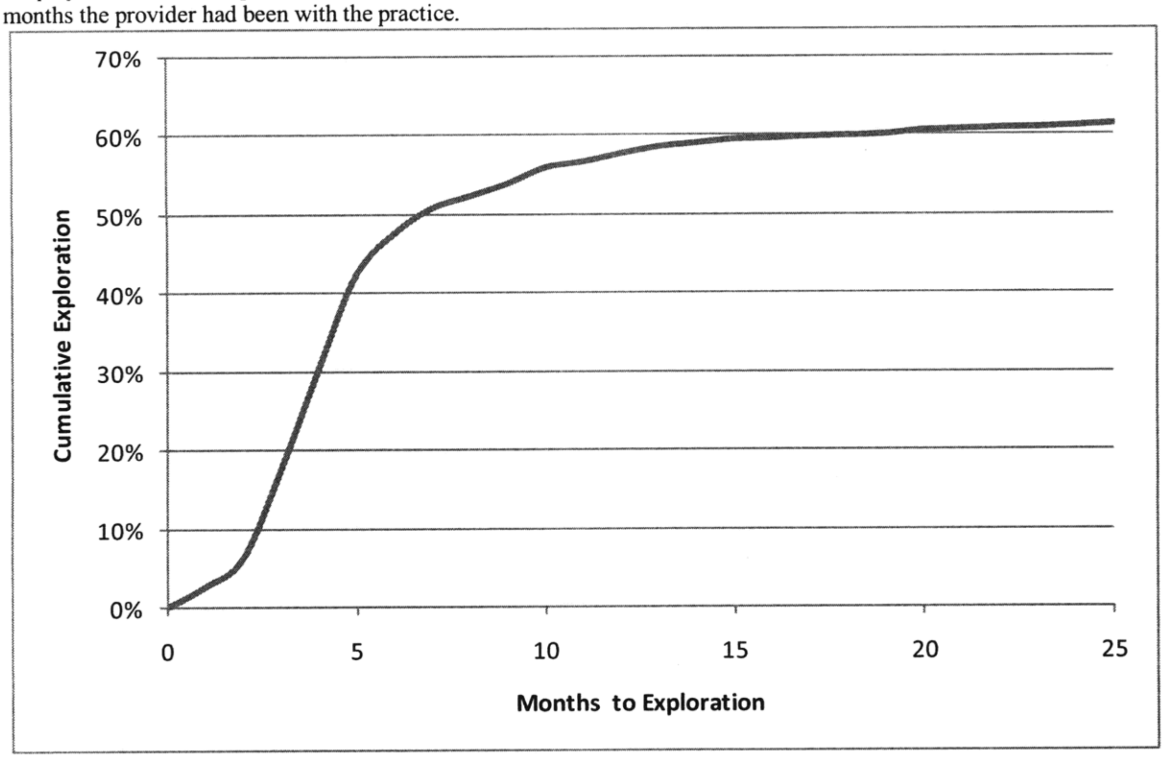
To understand adoption and information effects at the provider level, I looked at CPR adoption among clients who went live after January 1, 2007, and I observed the uptake of the CPR by the providers. For the purposes of this study, a medical provider was defined as a practice employee who provided billable clinical services. To be included, a provider had to be with their practice by October 1, 2008 and be active with the practice through March 1, 2009. In addition, to ensure that the included providers used athenaHealth's services in a consistent manner and that the providers were active throughout the study period, the provider had to average at least 20 appointments per month during the study period.

Exploration of the CPR by New Practices

I defined "exploration" as the first time a report for a given provider was accessed. I examined the length of time in months between when the physician first became active in the system and the time that the CPR report for that provider was explored. For consistency, I defined the provider's date of first activity as the date of the provider's first patient appointment resulting in billable activity.

The exploration curve of the CPR by providers in new practices displayed a sharp initial uptake, with a declining rate of exploration as time went on (Figure 2). Ultimately, 61% of the CPR reports for the providers in this study were accessed at least once during the study timeframe of January, 2007 through March, 2009. Using the Bass diffusion formula (Equation 1) and linear optimization, I estimated coefficients of external (p) and internal (q) influences to be 0.18 and -0.29 respectively.

Figure 2. Cumulative CPR Exploration Curve by All Providers
Displays the cumulative percent of medical providers whose CPR report had been accessed, as a function of the number of months the provider had been with the practice.



Exploration of the CPR by New Providers

I also examined if there was a different rate of exploration among those providers who joined practices after the practices were already athenaHealth clients, and providers who joined practices that had already explored the CPR. I defined a "new provider" as a provider who was entered into the system more than three months after the practice became an athenaHealth client. The cumulative exploration curve shows that there was little difference in the rate of exploration among all new providers compared with new providers who joined practices where other providers had explored the CPR (Figure 3). The estimated coefficients of external and internal influence also were similar (Table 4).

Figure 3. Cumulative CPR Exploration by New Providers
Displays the cumulative percent of providers who explored the CPR (n=358) to the cumulative exploration percent among providers who joined practices where other providers had already explored the CPR (n=265)

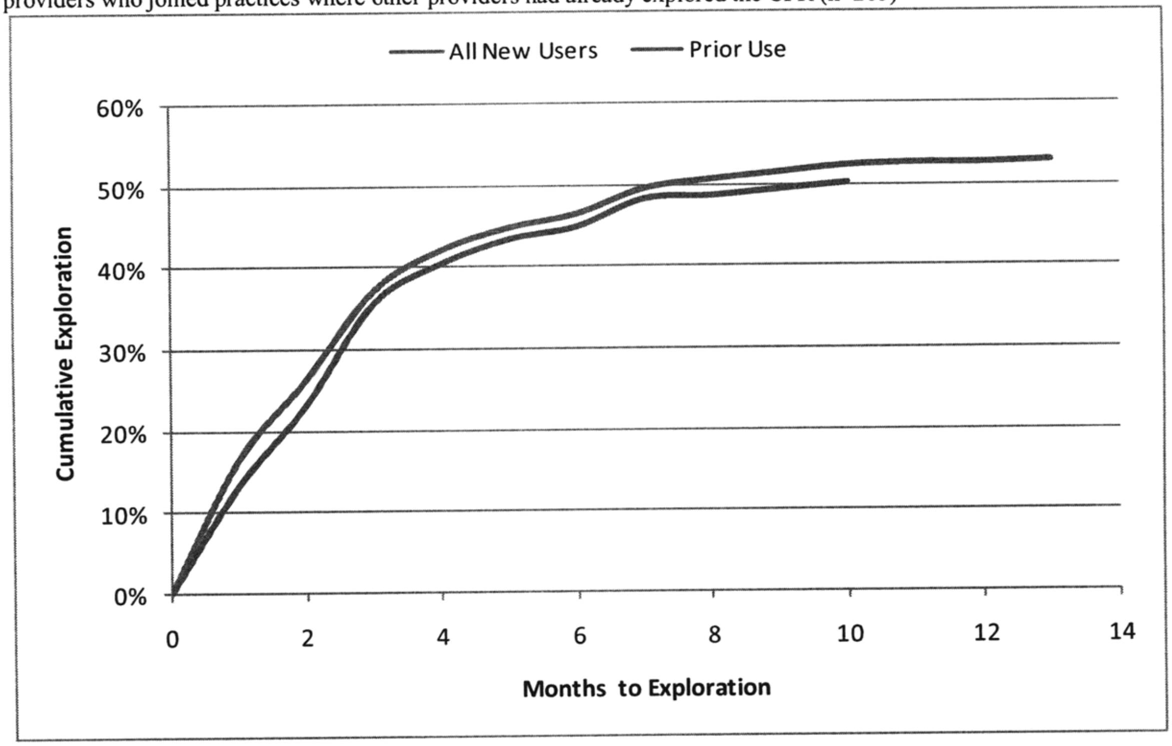


Table 4. Diffusion Coefficient Estimates
Technology diffusion model estimates for the CPR exploration curve for all providers, providers who joined existing practices, and providers who joined practices where other providers explored the CPR. Coefficients were estimated using linear optimization.

	Coefficient of external influence *(p)*	Coefficient of internal influence *(q)*
All Providers	0.18	-0.29
New Providers	0.20	-0.36
New Providers with Prior Exploration	0.19	-0.34

Factors Associated with Exploration

I created a multivariate model to determine if certain practice factors (region, practice size) or medical provider factors (specialty, provider type, provider activity level) were associated with exploring the CPR. Logistic regression using backwards elimination was used to determine the significant factors (Table 5). Pediatric providers were found to be more likely to explore the CPR (Odds=1.6, $p = 0.03$). Mid-level and staff providers were significantly less likely to explore the CPR (Odds=0.5 and 0.2 respectively, $p<0.001$). In addition, regional variation and practice size factors were observed. Activity level in terms of appointments per month was also a significant factor. Providers who explored the CPR saw more patients per month: 207 (95% C.I. 200-213) vs. 156 (95% C.I.149-163).

Table 5. Factors Associated with CPR Exploration
P-Values were calculated using a multivariate logistic regression model using backwards elimination. Practice size, specialty, provider type, region and appointments per month were included in the model.

Variable	Odds Ratio	Std. Err.	P>|z|	95% Conf. Interval
Practice Size				
1 to 3*	1			
6 to 10	0.668	0.080	0.001	(0.528 to 0.845)
>50	0.816	0.069	0.017	(0.691 to 0.964)
Specialty				
Primary Care*	1			
Other-N/A	0.732	0.103	0.027	(0.556 to 0.965)
Pediatric Medicine	1.563	0.322	0.03	(1.044 to 2.340)
Provider Type				
Doctor*	1			
Mid-Level	0.539	0.051	<0.001	(0.448 to 0.649)
Staff	0.203	0.044	<0.001	(0.132 to 0.311)
Region				
Northeast*	1			
Midwest	1.504	0.170	<0.001	(1.206 to 1.877)
West	1.438	0.129	<0.001	(1.206 to 1.714)
Appointments Per Month	1.003	0.000	<0.001	(1.002 to 1.004)

* Baseline category

I also examined the factors influencing new providers who joined existing practices. In this analysis, I included another variable, the percentage of practices providers' CPRs that had been explored at the time a new provider joined a practice. I then examined whether this was different among new providers who explored the CPR vs. those that did not. I wanted to answer the question: if a significant portion of a practice's providers had explored the CPR, were new providers more likely to explore it? Although I found that the percentage of prior access was slightly higher among new providers who explored the CPR, this difference was not significant (Table 6). In addition, when adjusted for specialty, region, provider type and activity level, the prior utilization in the practice did not emerge as a significant factor.

Table 6. New Provider Prior Utilization Percentage
P-value was calculated using a two-sample t-test with equal variances, testing the mean percentage of prior CPR exploration at the time a new provider joined a practice.

Group	N	Mean	Std. Dev.	95% Confidence Interval	
Explored?					
No	168	0.31	0.27	0.27	0.35
Yes	191	0.32	0.31	0.27	0.36
Pr(|T| > |t|) = 0.818					

Utilization of the CPR

While exploration of the CPR report is important, it is the incorporation of this information into the provider's regular practice that will have an impact. To measure this, I looked at CPR utilization on a monthly basis among the population of providers that explored the CPR. I defined the utilization percentage for a given provider as the number of unique monthly CPR reports that were viewed divided by the number of months a provider was active. I defined a "heavy user" as one who accessed more than 50% of the available monthly reports during the provider's active period. Of the 3,230 providers, 1,983 went on to utilize it at least once, and 403 went on to become heavy users. This represents 12.5% of the study population, and 20% of the explorer population.

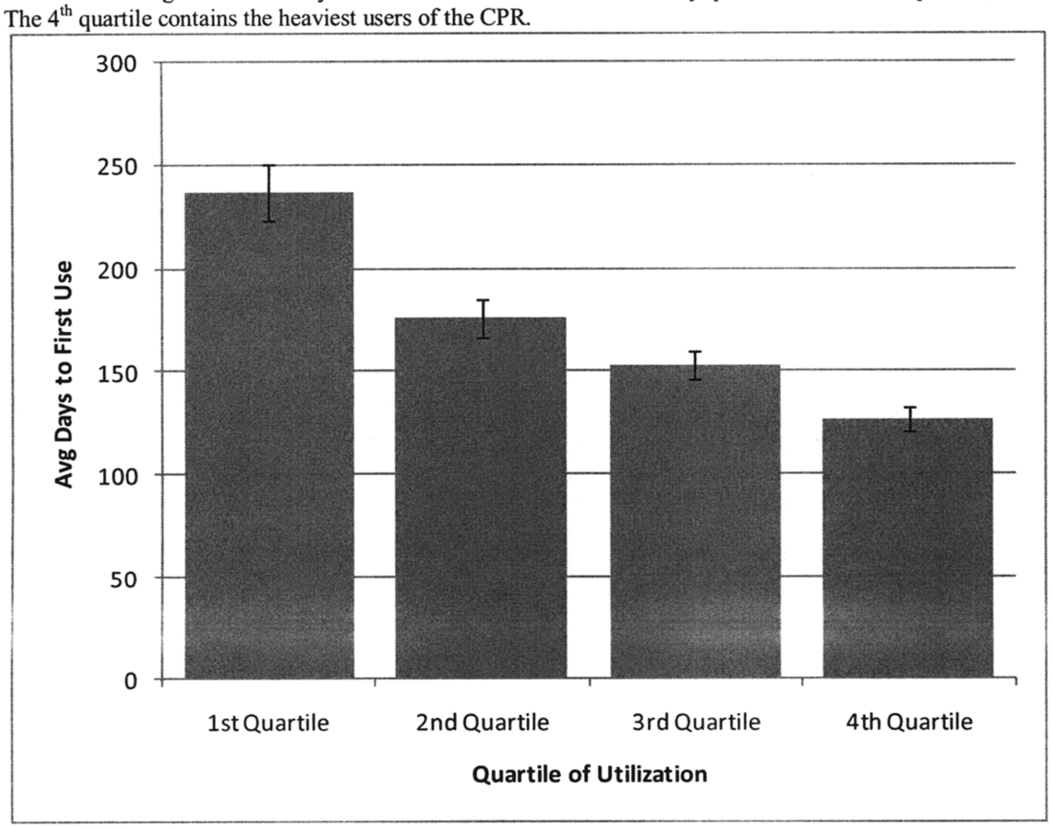
Using backwards elimination on a multivariate linear regression model with a $p<0.05$ cutoff, I created a model showing the significant factors relating to utilization (Table 7). The provider type again emerged as a significant factor, as well as practice size > 50. Medical specialties tended to utilize the report slightly less. Also, the number of days to the first use of the report emerged as a significant factor; exploring the CPR earlier led to higher utilization. Providers in the highest quartile of use accessed the CPR 113 days earlier compared with the lowest quartile of use (Figure 4).

Table 7. Factors Relating to CPR Utilization
Results of a multivariate analysis using linear regression using backwards elimination and a $p<0.05$ cutoff. The following variables were included: region, provider type, practice size, specialty and the number of days to first use.

Variable	Coefficient	Std. Err.	P>|t|	95% Conf. Interval
Practice Size				
1 to 3*	0			
>50	0.104	0.010	<0.001	(0.084 to 0.123)

Specialty				
Primary Care*	0			
Medical Specialty	-0.036	0.010	<0.001	(-0.056 to -0.016)
Provider Type				
Doctor*	0			
Mid-Level	-0.102	0.012	<0.001	(-0.125 to -0.078)
Staff	-0.202	0.038	<0.001	(-0.275 to -0.128)
Days To First Use	-0.001	0.000	<0.001	(-0.001 to -0.001)
Constant	0.438	0.010	<0.001	(0.418 to 0.457)
* Baseline category				

Figure 4. Days to First Use by Quartile of Utilization
Shows the average number of days before the CPR was first accessed by quartile of utilization percent, as well as the 95% C.I. The 4th quartile contains the heaviest users of the CPR.



Use of the CPR and Performance

I divided the provider population into three classifications: heavy user (>50% utilization), light-user (<=50% utilization) and non-user. In addition, to ensure a more accurate comparison, providers with missing performance data were eliminated. I compared the classifications across four performance metrics, two financial (days in accounts receivable and work RVUs per month) and two operational (denial rate per appointment and hold lag).

After eliminating providers with missing performance data, I was left with a provider population of 3,175 (Table 8). I found that heavy CPR users performed better in the hold lag metric and had more work RVUs per month (Figure 5 and Figure 6). There was a trend towards improved Days in Accounts Receivable, although this was not statistically significant (Figure 7). Interestingly, the denial rate showed a trend in the opposite direction, with heavy utilization associated with worse performance, although this was not statistically significant (Figure 8).

I tested whether utilization was a significant factor after adjusting for specialty, practice size and provider type by running a multivariate analysis. After running a regression with backwards elimination, utilization was the most significant factor relating to an improvement in hold lag (Table 9). Utilization was also significant with regard to improvements in DAR and Work RVU after adjusting for specialty, practice size and provider type (Table 10 and Table 12), and was associated with a slightly worse denial rate (Table 11).

Table 8. Provider Characteristic in CPR Performance Evaluation
Characteristics of different types of users of the CPR. Heavy use of the CPR is defined as using the report >50% of the months it was available; light use is defined as use of <= 50%.

Variable	Non-User		Light User		Heavy User	
	N	%	N	%	N	%
Region						
Midwest	178	34%	226	43%	120	23%
Northeast	224	38%	309	53%	54	9%
South	444	40%	541	49%	120	11%
West	345	36%	497	52%	117	12%
Practice Size						
1 to 3	149	32%	269	58%	47	10%
4 to 5	78	41%	95	50%	18	9%
6 to 10	166	43%	186	48%	33	9%
11 to 50	309	33%	534	57%	86	9%
> 50	489	41%	489	41%	227	19%
Provider Type						

Doctor	745	32%	1,205	52%	372	16%
Mid-Level	386	50%	347	45%	38	5%
Staff	60	73%	21	26%	1	1%
Specialty Type						
Cardiology	54	30%	121	67%	6	3%
Medical Specialty	464	45%	458	45%	107	10%
OB/GYN	68	32%	106	49%	41	19%
Orthopedic Surgery	130	35%	178	48%	61	17%
Other-N/A	71	45%	83	52%	5	3%
Pediatric Medicine	34	23%	95	63%	21	14%
Primary Care	284	35%	406	50%	129	16%
Surgical Specialty	86	34%	126	50%	41	16%
Total	1191	38%	1573	50%	411	13%

Figure 5. Average Hold Lag by CPR Utilization
Average performance on the hold lag metric, by utilization group; lower is better. 95% C.I. is shown.

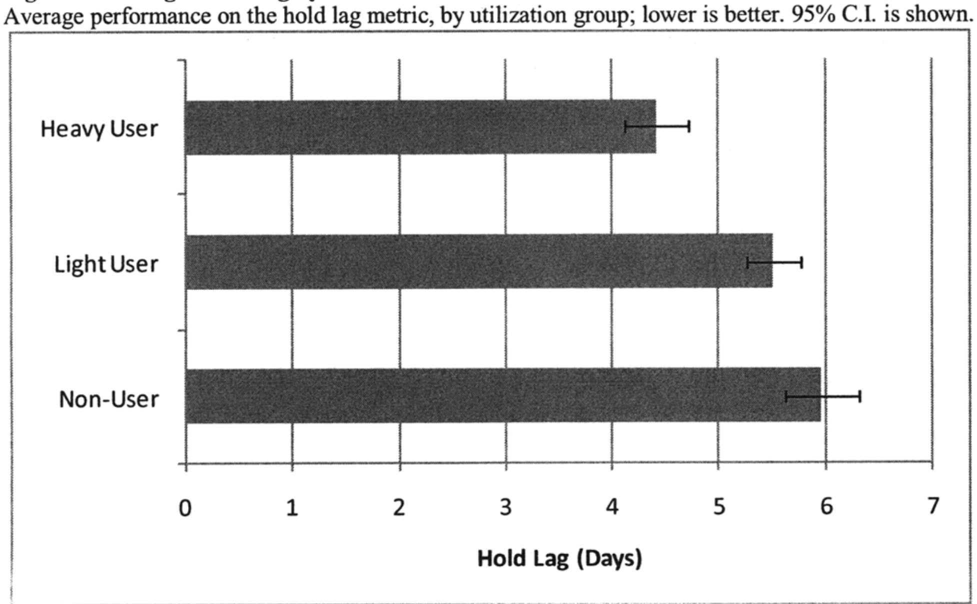


Figure 6. Average Work RVUs per Month by CPR Utilization
Average work RVUs per month by utilization group; higher is better. 95% C.I is shown.

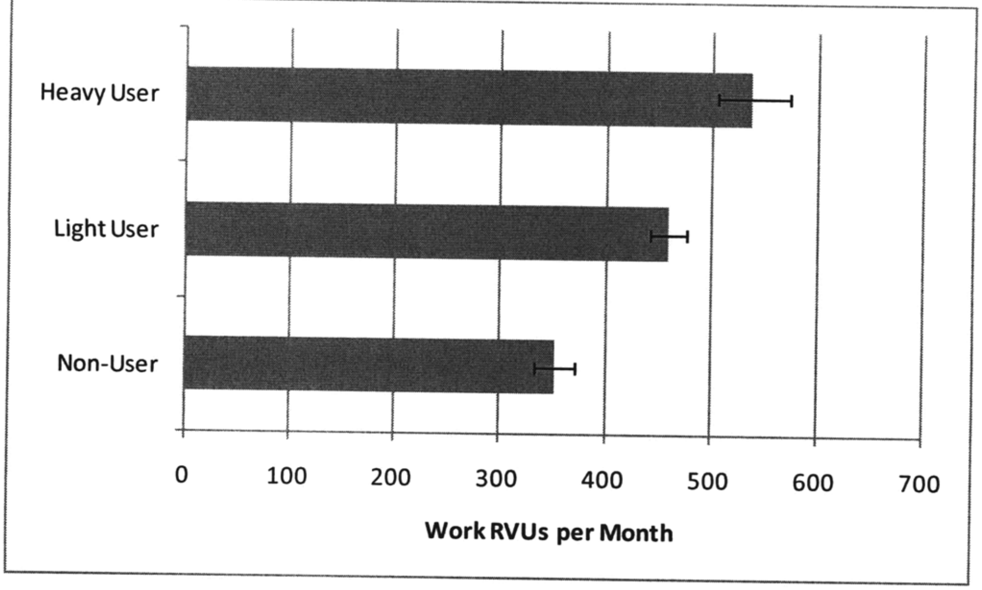


Figure 7. Days in Accounts Receivable by CPR Utilization
Average days in accounts receivable by utilization group; lower is better. 95% C.I. is shown.

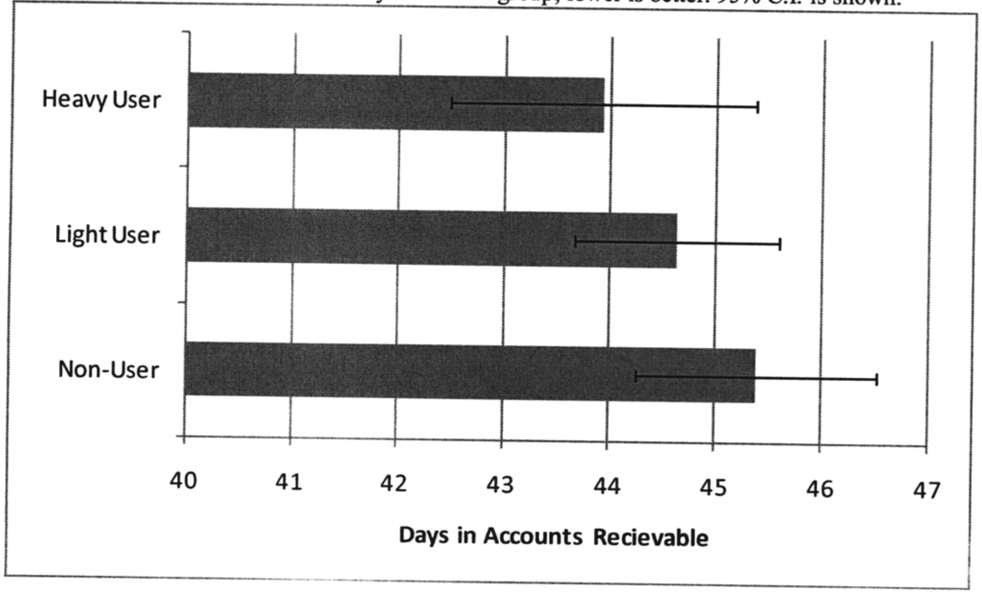


Figure 8. Denial Rate per Appointment by CPR Utilization
Average number of denials per appointment by utilization group; lower is better. 95% C.I. is shown.

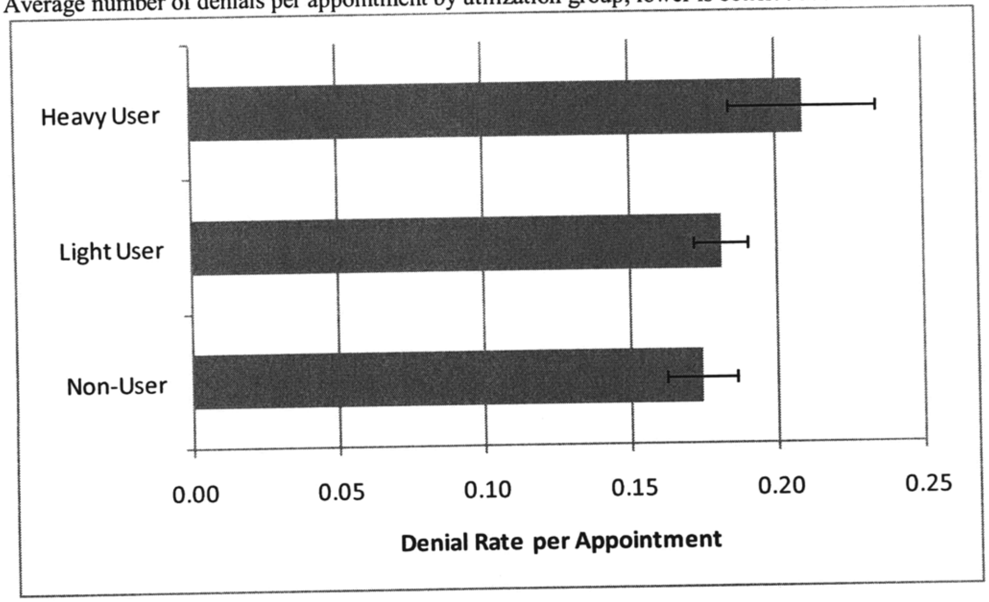


Table 9. Variables Associated with Hold Lag in New Practices
Results of a multivariate analysis using linear regression and backwards elimination with a $p<0.05$ cutoff. Shows factors associated with hold lag among providers in new practices; lower coefficients are better. Variables included were: provider type, practice size, specialty, and CPR utilization.

Variable	Coefficient	Std. Err.	P Value	95% C.I.
Provider Type				
Doctor*	0			
Mid-Level	-0.573	0.229	0.012	(-1.022 to -0.124)
Practice Size				
1 to 3*	0			
6 to 10	-1.977	0.339	<0.001	(-2.641 to -1.313)
11 to 50	-1.133	0.270	<0.001	(-1.661 to -0.604)
>50	-1.295	0.259	<0.001	(-1.803 to -0.786)
Specialty				
Primary Care*	0			
Cardiology	-0.831	0.411	0.043	(-1.637 to -0.025)
Surgical Specialty	-0.778	0.349	0.026	(-1.463 to -0.093)
Utilization	-2.612	0.393	<0.001	(-3.382 to -1.841)
Constant	7.364	0.226	<0.001	(6.921 to 7.807)

* Baseline category

Table 10. Factors Associated with DAR in New Practices
Results of a multivariate analysis using linear regression and backwards elimination with a p<0.05 cutoff. Shows factors associated with days in accounts receivable among providers in new practices; lower coefficients are better. Variables included were: provider type, practice size, specialty, and CPR utilization.

Variable	Coefficient	Std. Err.	P Value	95% C.I.
Provider Type				
Doctor*	0			
Staff	-4.902	2.129	0.021	(-9.076 to -0.728)
Practice Size				
1 to 3*	0			
6 to 10	-4.689	1.033	<0.001	(-6.714 to -2.664)
Specialty				
Primary Care*	0			
Cardiology	-4.701	1.524	0.002	(-7.690 to -1.712)
Medical Specialty	-3.406	0.838	<0.001	(-5.049 to -1.764)
Orthopedic Surgery	-3.031	1.145	0.008	(-5.276 to -0.787)
Other-N/A	-3.931	1.615	0.015	(-7.096 to -0.765)
Pediatric Medicine	-8.6	1.650	<0.001	(-11.835 to -5.364)
Surgical Specialty	3.438	1.325	0.010	(0.840 to 6.037)
Utilization	-3.853	1.403	0.006	(-6.603 to -1.103)
Constant	48.333	0.691	<0.001	(46.979 to 49.687)
* Baseline category				

Table 11. Factors Associated with Denial Rate in New Practices
Results of a multivariate analysis using linear regression and backwards elimination with a p<0.05 cutoff. Shows factors associated with the per appointment denial rate among providers in new practices; lower coefficients are better. Variables included were: provider type, practice size, specialty, and CPR utilization.

Variable	Coefficient	Std. Err.	P Value	95% C.I.
Provider Type				
Doctor*	0			
Mid-Level	-0.051	0.01	<0.001	(-0.070 to -0.032)
Specialty				
Primary Care*	0			
Cardiology	0.185	0.016	<0.001	(0.153 to 0.216)
Medical Specialty	0.057	0.009	<0.001	(0.041 to 0.074)
OB/GYN	-0.043	0.015	0.003	(-0.072 to -0.015)
Other-N/A	0.048	0.018	0.008	(0.012 to 0.084)
Utilization	0.062	0.015	<0.001	(0.032 to 0.091)

Constant	0.153	0.006	<0.001	(0.141 to 0.166)
* Baseline category				

Table 12. Factors Associated with Work RVU in New Practices
Results of a multivariate analysis using linear regression and backwards elimination with a p<0.05 cutoff. Shows factors associated with the average monthly work RVU among providers in new practices; higher coefficients are better. Variables included were: provider type, practice size, specialty, and CPR utilization.

Variable	Coefficient	Std. Err.	P Value	95% C.I.
Provider Type				
Doctor*	0			
Mid-Level	-239.554	14.546	<0.001	(-268.074 to -211.034)
Staff	-321.969	34.282	<0.001	(-389.187 to -254.751)
Practice Size				
1 to 3*	0			
4 to 5	-89.040	23.981	<0.001	(-136.060 to -42.021)
11 to 50	-48.248	14.329	0.001	(-76.343 to -20.153)
>50	-99.448	13.657	<0.001	(-126.225 to -72.671)
Specialty				
Primary Care*	0			
Cardiology	373.136	24.777	<0.001	(324.556 to 421.716)
Medical Specialty	207.516	14.641	<0.001	(178.810 to 236.223)
OB/GYN	140.426	22.965	<0.001	(95.397 to 185.454)
Orthopedic Surgery	377.397	18.762	<0.001	(340.610 to 414.184)
Other-N/A	146.497	27.922	<0.001	(91.749 to 201.244)
Pediatric Medicine	71.244	26.587	0.007	(19.114 to 123.374)
Surgical Specialty	333.806	21.550	<0.001	(291.552 to 376.060)
Utilization	199.725	22.639	<0.001	(155.336 to 244.114)
Constant	334.040	14.515	<0.001	(305.580 to 362.499)
* Baseline category				

Practice Exploration and Use of Report Builder

To understand adoption and use at the practice level, I studied the Report Builder feature. This feature was released in May, 2007, and it allows practices to create custom reports on their practice data. Prior to this, there were a number of predefined reports that were provided by athenaHealth; custom reports were created on an individual basis for clients. Some of these predefined reports were incorporated into the Report Builder feature so that clients who previously used a predefined report on a regular basis would now use it through the Report Builder feature, which brought with it extra customization and display options.

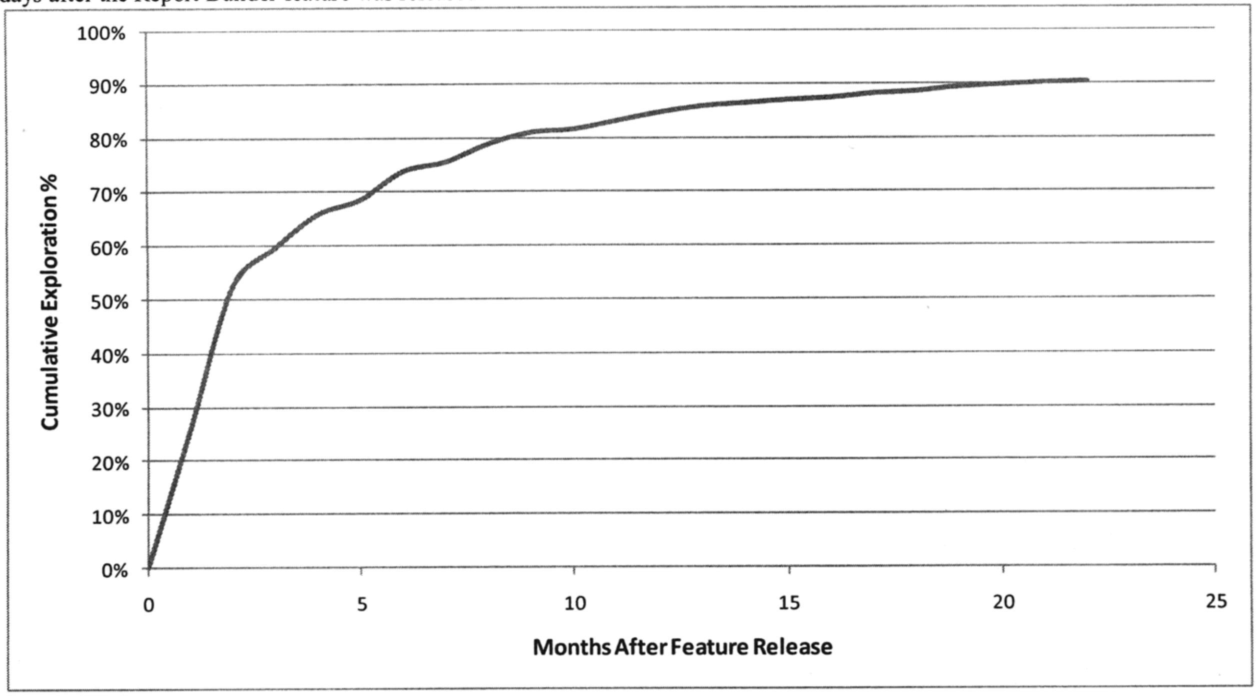
There are a variety of users of the Report Builder feature. Operational reports might be run by the office staff. Larger practices with a dedicated management staff would typically run the higher level financial reports; in smaller practices, the physicians themselves might be the user. There was no fee for using the Report Builder feature; it was included in the regular software updates that all practices receive automatically.

To examine the Report Builder feature, I used the set of practices that were using the software as of January 1, 2007. In addition, there were a small number of practices that beta-tested the feature before its release; these practices were excluded.

Exploration of Report Builder

I defined Report Builder exploration as the first time a person from a practice accessed the Report Builder feature, based on web log data up to October 1, 2008. Overall, the cumulative exploration curve exhibited a sharp initial uptake, with a declining rate of penetration as time went on (Figure 9). It took only 2 months for 50% of the practices to try the feature at least once. However, it took 7 months to achieve 75%. As of October 1, 2008, 88% of these practices had used the feature at least once. Using linear optimization, the coefficient of internal *(p)* and external *(q)* influence were calculated to be 0.36 and -0.35 respectively.

Figure 9. Report Builder Cumulative Exploration Percentage
Displays the cumulative percent of practices that tried the Report Builder feature at least once, as a function of the number of days after the Report Builder feature was released.



Factors Associated with Exploration

I ran a multivariate analysis to examine the practice factors associated with the exploration of the feature, as well as exploration in the first 30 days – "early explorers"(Table 13 and Table 14). Practice size of more than 5 physicians was associated with exploring the feature as well as being an "early explorer". In addition, certain practices (OB/GYN and Pediatric Medicine) were associated with early exploration. Region and the length of time as a client were other variables I explored, and were not found to be significant factors.

Table 13. Factors Associated with Practice Exploration of Report Builder
Significant factors associated with exploration of the Report Builder were determined with a multivariate model using logistic regression and backwards elimination. Variables included in the model were: practice size, specialty, region, and the number of months as a client.

Variable	Odds Ratio	Std. Err.	P>|z|	95% Conf. Interval
Practice Size				
1-3*	1			
6-10	12.612	13.016	0.014	(1.668 to 95.338)
11-50	23.481	27.102	0.006	(2.445 to 225.528)
Specialty				

Multispecialty	0.162	0.140	0.036	(0.030 to 0.886)
* Baseline category				

Table 14. Factors Associated with Early Exploration of Report Builder
Significant factors relating to early exploration (within 30 days) of the Report Builder feature were determined with a multivariate model using logistic regression and backwards elimination. Variables included in the model were: practice size, specialty, region, and the number of months as a client.

Variable	Odds Ratio	Std. Err.	P>|z|	95% Conf. Interval
Practice Size				
1-3*	1			
6-10	4.236	1.282	<0.001	(2.340 to 7.666)
11-50	10.882	4.159	<0.001	(5.145 to 23.014)
Specialty				
OB/GYN	2.030	0.546	0.009	(1.198 to 3.440)
Pediatric Medicine	3.962	1.459	<0.001	(1.925 to 8.155)
* Baseline category				

Utilization of Report Builder

A feature such as custom reporting, despite providing valuable information, is not an integral part of practices' day to day operations. Therefore I decided to look at effective use of this feature on a monthly scale, and measure the number of months that a practice utilized this feature, beginning with the month that it first used it. The question is essentially: once the practice tried this feature, did it incorporate it into its monthly operations?

The practices were roughly evenly distributed in their utilization of the Report Builder feature after using it once (Figure 10). 236 practices used it more than 50% of the months in the study period after using it once ("heavy users"); 218 practices used it 50% or less ("light users"). Heavy users represented 46% of the study population, and 52% of the explorer population.

I ran a multivariate analysis to look at factors related to heavy utilization of the report after exploration. These included the practice factors studied previously, as well as the length of time the practice waited before trying the Report Builder feature. Practice size of greater than 3 and exploring the feature earlier were significant factors related to heavy use (Table 15). 100% of multispecialty practices were heavy users; OB/GYN practices were less likely to be heavy users.

Table 15. Factors Related To Heavy Report Builder Utilization
Heavy utilization was defined as use during >50% of months during the study period. Factors were determined through a multivariate analysis using logistic regression and backwards elimination. Variables included practice size, region, specialty, months as client and months to first use of the feature.

Variable	Odds Ratio	Std. Err.	P>|z|	95% Conf. Interval
Practice Size				
1-3*	1			
4-5	3.495	1.286	0.001	(1.699 to 7.189)
6-10	3.611	1.162	<0.001	(1.922 to 6.786)
11-50	5.987	2.521	<0.001	(2.623 to 13.668)
Specialty				
Primary Care*	1			
OB/GYN	0.479	0.148	0.018	(0.261 to 0.880)
Months To First Use	0.83	0.032	<0.001	(0.769 to 0.895)
* Baseline category				

Figure 11 shows the association between utilization and days to first use in more detail. Those practices in the top two quartiles of use (practices that used the report more than 50% of the months) had a significantly lower delay in first exploring the report feature compared with those in the bottom two quartiles of use.

Figure 10. Report Builder Monthly Utilization after First Use
Shows a histogram of the practices, grouped by the percentage of months that a practice accessed the Report Builder feature after trying for the first time. For example, a practice that used the Report Builder feature for the first time in January, 2008, and then used it four other months between then and October 2008 would have a utilization of 50%.

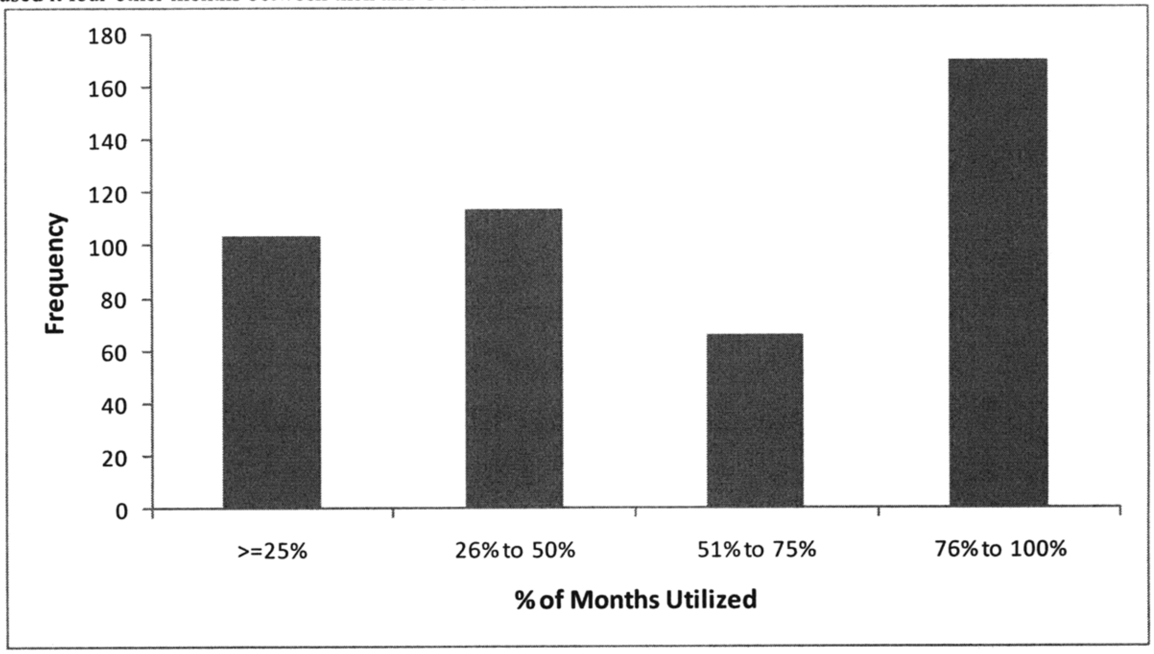
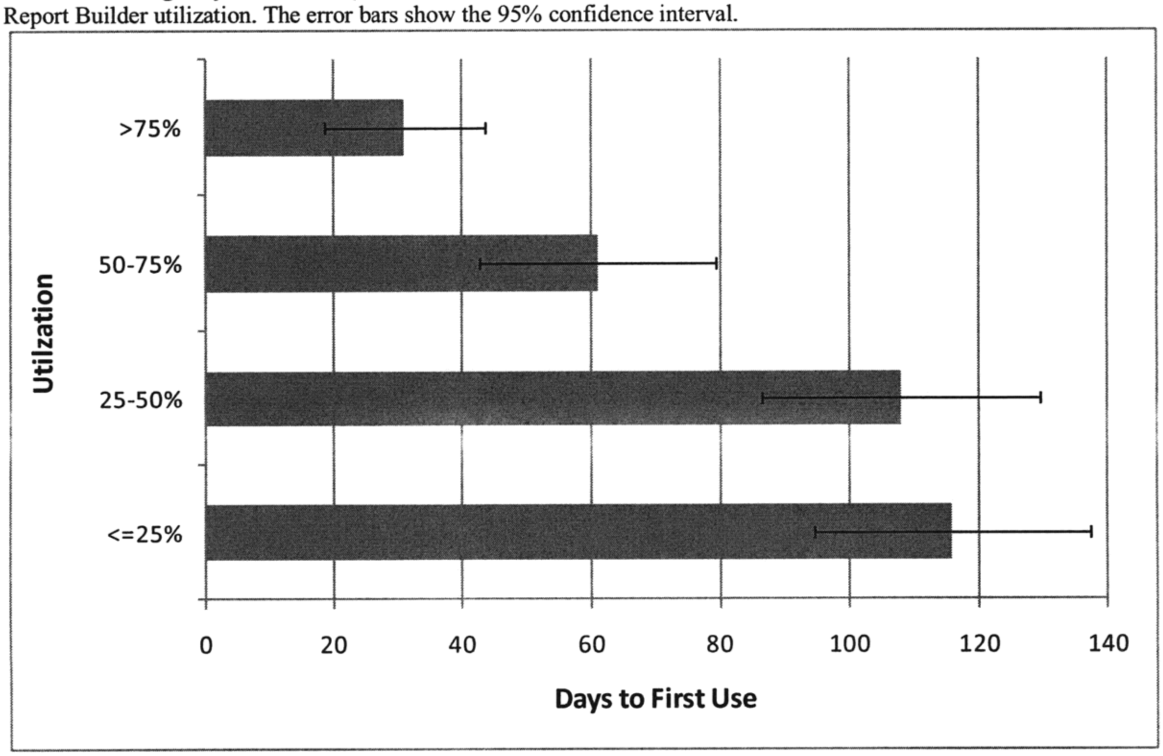


Figure 11. Report Builder Utilization and Days to First Use
Shows the average days to first use (measured in the number of days until the Report Builder feature was first used) by quartile of Report Builder utilization. The error bars show the 95% confidence interval.



Relationship to Performance

As mentioned earlier, information alone is rarely valuable. It is the actions that it inspires and the incentives that it creates that are the most telling and interesting. First, I examined whether higher performing practices were more likely to utilize the report builder heavily. I examined three performance indicators, DAR, hold lag and denial rate (Work RVUs were excluded since this was not normalized for practice size) in the five month period prior to the release of the feature. All practices were ranked on a scale of 1 to n on these three metrics, with the best performer in a given metric receiving a 1, the next best a 2, and so on. A basic analysis indicated that future utilization of the Report Builder was associated with a better hold lag and DAR ranking (Table 16). However, when adjusted for practice size, specialty, and region, this effect was not present.

Table 16. Performance Rank Prior to Utilization
Shows the rank (lower is better) across three metrics in the five month period before the Report Builder feature was released, by future utilization of the feature. Heavy usage was defined as >50% of months.

usage	N	Avg. Hold Rank	Avg. DAR Rank	Avg. Denial Rate Rank
heavy	192	228	226	251
light	218	223	227	216
none	51	276	268	215

Next, I looked at whether utilization of the Report Builder feature was associated with improved performance during the study period. I ran a multivariate analysis looking at multiple factors relating to the performance metrics described above: DAR, hold lag, denial rate and work RVU. Included in this model was the utilization, which was defined as the number of months that a practice accessed the Report Builder feature during the study period of May 2007 to October 2008. Utilization of the feature was significantly associated with better performance in the DAR, hold lag, and work RVU metrics (Table 17, Table 18 and Table 20). However, utilization was associated with a slightly worse denial rate (Table 19).

Table 17. Factors Associated with Hold Lag in Existing Practices
Results of a multivariate analysis of hold lag performance using linear regression and backward elimination with a $p < 0.05$ cutoff. Shows factors related to hold lag performance among existing practices; lower coefficients are better. Variables included in the model were: region, specialty, size, and Report Builder utilization during the period May, 2007 through October, 2008.

Variable	Coefficient	Std. Err.	P Value	95% Conf. Interval
Specialty				
Primary Care*	0			
Multispecialty	10.274	3.334	0.002	(3.723 to 16.825)

Utilization	-7.18	1.829	<0.001	(-10.773 to -3.586)
Constant	11.16	1.024	<0.001	(9.147 to 13.173)
* Baseline category				

Table 18. Factors Associated with DAR in Existing Practices
Results of a multivariate analysis of days in accounts receivable performance using linear regression and backward elimination with a $p < 0.05$ cutoff. Shows factors related to days in accounts receivable performance among existing practices; lower coefficients are better. Variables included in the model were: region, specialty, size, and Report Builder utilization during the period May, 2007 through October, 2008.

Variable	Coefficient	Std. Err.	P Value	95% Conf. Interval
Specialty				
Primary Care*	0			
Multispecialty	16.893	5.783	0.004	(5.527 to 28.258)
Surgical Specialty	10.488	2.765	<0.001	(5.054 to 15.922)
Region				
Northeast*	0			
West	7.01	3.14	0.026	(0.840 to 13.180)
Utilization	-8.006	3.177	0.012	(-14.250 to -1.762)
Constant	42.726	1.954	<0.001	(38.885 to 46.567)
* Baseline category				

Table 19. Factors Associated with Denial Rate in Existing Practices
Results of a multivariate analysis of the per appointment denial rate using linear regression and backward elimination with a $p < 0.05$ cutoff. Shows factors related denial rate performance among existing practices; lower coefficients are better. Variables included in the model were: region, specialty, size, and Report Builder utilization during the period May, 2007 through October, 2008.

Variable	Coefficient	Std. Err.	P Value	95% Conf. Interval
Specialty				
Primary Care*	0			
OB/GYN	-0.017	0.007	0.014	(-0.031 to -0.003)
Region				
Northeast*	0			
South	0.013	0.006	0.021	(0.002 to 0.025)
Utilization	0.019	0.007	0.008	(0.005 to 0.033)
Constant	0.076	0.004	<0.001	(0.067 to 0.085)
* Baseline category				

Table 20. Factors Associated with Work RVU in Existing Practices
Results of a multivariate analysis of the average monthly work RVUs using linear regression and backward elimination with a p < 0.05 cutoff. Shows factors related to work RVU performance among existing practices; lower coefficients are better. Variables included in the model were: region, specialty, size, and Report Builder utilization during the period May, 2007 through October, 2008.

Variable	Coefficient	Std. Err.	P Value	95% Conf. Interval
Practice Size				
1-3*	0			
4-5	20,030	10,189	0.05	(7 to 40,054)
6-10	64,932	9,923	<0.001	(45,431 to 84,433)
11-50	193,897	10,881	<0.001	(172,514 to 215,281)
>50	470,239	22,548	<0.001	(425,927 to 514,552)
Specialty				
Primary Care*	0			
Medical Specialty	25,263	7,569	0.001	(10,388 to 40,139)
OB/GYN	25,796	9,127	0.005	(7,860 to 43,733)
Surgical Specialty	50,574	8,348	<0.001	(34,169 to 66,979)
Utilization	39,136	10,136	<0.001	(19,217 to 59,056)
Constant	-10,556	6,609	0.111	(-23,544 to 2,433)
* Baseline category				

To detect whether the use of the Report Builder feature had a direct impact on performance, I studied financial and operation performance for a period of five months before the release of the feature (January, 2007 through May, 2007) and compared that to the same period the following year (January, 2008 through May, 2008). For each practice, I calculated the percentage change across four performance metrics: DAR, hold lag, denial rate and work RVUs per month. Again, in this basic analysis improved performance in all but work RVUs seemed to be present, but was not significant after adjusting for other factors (Table 21).

Table 21. Report Builder Use and Change in Performance
Shows the percentage change across four performance metrics from the period five months prior to the release of report builder and the same period in the next year after the release. Lower percentage change is better for hold lag, DAR and denial rate; higher is better for work RVU.

usage	Freq.	% Change in Hold Lag	% Change in DAR	% Change in Denial Rate	% Change in Work RVU per Month
heavy	192	12.9%	1.2%	-4.8%	3.7%
light	218	56.8%	1.4%	-11.9%	2.2%
none	51	57.8%	2.7%	8.8%	6.2%

Discussion

This pilot study shows that the challenges of healthcare information technology adoption do not end once the check is written for the purchase of a health IT system. Of the two features that I investigated in this study, the more successful feature only achieved 88% penetration (defined as using the feature at least once) after being available to these practices for over a year. This observation occurred despite the fact that these features were free to the practices and could have a significant impact on their finances and operations.

However, similarities in adoption provide insight into whom to target with new initiatives and the rate of uptake, whether looking at the practice or the individual provider. Early adopters were true to their label; whether it was new capabilities given to the existing client base or new providers coming on to the system, a significant proportion of adoption took place early on. These early adopters went on to use the functionality more often and truly made it part of their practice.

The implications of this study are most significant for policy makers and health IT vendors. The government is investing a considerable amount of money to ensure the computerization of medical records, and this study implies that incentives will need to be in place to encourage the utilization of beneficial features. Health IT vendors should be aware that only a limited set of the functionality is used, and if clients are to realize the full value of their purchase, then more effort should be expended in introducing new functionality to both new and existing clients. Further studies are recommended to examine clinical features and endpoints in a broader range of settings to better understand the dynamics of adoption.

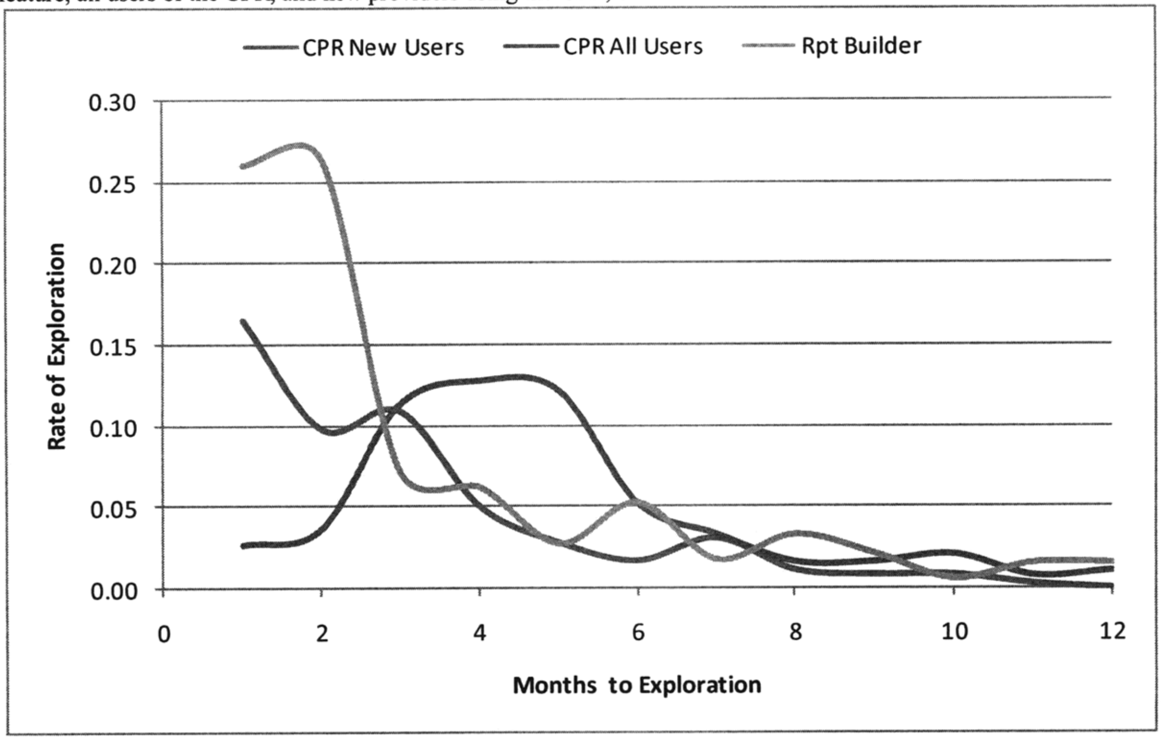
Similarity in Adoption Patterns

Even when looking at different populations, organizational units (practice vs. provider), and adoption scenarios (new users adopting existing functionality vs. existing users adopting new functionality), there was a strong similarity in adoption patterns. This observation is evidenced by the similar estimated coefficients of innovation (p) and imitation (q), which averaged 0.25 and -0.32 respectively. These findings are higher than the coefficient of innovation estimated for medical technology such as EHR's ($p=0.0054$) and CT scanners ($p=0.036$)[31,32]. This coefficient value more closely resembles decision making tools such as calculators ($p=0.143$) and personal computers (p=0.121).[32] This finding would be expected given that there is no cost to use these features, and that the providers have already achieved a certain level of comfort with the system, as they have made the decision to purchase and install it.

The low social or imitation factor was also of interest. For comparison, medical technologies such as EHRs (q=.1673) and ultrasound (q=0.510) exhibit a much greater social aspect, which is understandable given the higher barrier to adoption in terms of cost and organizational acceptance that must be overcome. The fact that social interaction at the practice and provider level displayed a similar lack of impact was unexpected. One would assume that when a provider joins a practice where the feature is utilized by the existing providers, that provider would then be more likely to utilize the feature. However, this proved to not be the case.

Another way to examine the similarity of adoption is by examining the slopes of the exploration curves. Once the growth of exploration had reached its peak (defined as a growth rate of < 10%), the rate of growth over the next 12 months was similar among practices that used Report Builder (slope of 0.023), providers using the CPR (0.012) and new practices' providers using the CPR (0.012) (Figure 12). The number of months to reach the peak exploration was also in a limited range of 3-5 months. While the overall level of exploration will depend on the perceived usefulness of the feature to the organization, patterns of exploration appear to be similar.

Figure 12. Exploration Growth Rate in Various Scenarios
Shows the rate of growth in cumulative exploration (given by the differential equation dGrowth/dt) for the Report Builder feature, all users of the CPR, and new providers using the CPR, over time.



Variation in Adoption Patterns

Whereas the patterns of adoption were similar, the factors influencing exploration and utilization varied. Practice size emerged as a significant factor associated with an increased likelihood of exploration and utilization in the Report Builder example. At the provider level however, practice size was associated with a lower likelihood of using the CPR.

One potential explanation for this finding may be the difference in group (practice vs. provider) as well as the nature of the features. Larger practices are more likely to have staff members dedicated to financial and operational issues with the capabilities to create custom reports through the Report Builder feature. Smaller practices might rely on the CPR for the provider level metrics, forgoing the customization enabled in Report Builder due to time or resource constraints.

This finding also hints at a potential paradox in health IT adoption. Many studies have shown that larger practices are more likely to purchase health IT systems due to increased financial and institutional resources. Once in place however, organizational dynamics and individual tendencies towards innovation come into play. These results hint that the advantage of effective use ends at the organizational level. Practitioners in smaller offices may be more likely to utilize health IT if the financial advantage of larger practices is not present.

This effect could be due to the different financial incentives present in small vs. large practices. Larger practices are more likely to have salaried physicians who have less of a direct incentive to concern themselves with the financial and operational aspects of the practice, whereas a smaller practice is more likely to be physician owned.

Adoption Levels Achieved

This study looked at health IT features that had no cost to adoption, but also had no explicit monetary incentives associated with these features. Since these features allow the practices and providers to examine their operational and financial performance, it can be assumed that examining this information may lead to improvements in these areas through the identification of problems. Despite this potential benefit, only a subset of providers appear to have incorporated these features into their practices. Of the providers who used the feature at least once, only 20% (CPR) and 46% (Report Builder) went on to utilize these features regularly (more than 50% of the months in the study period). This difference can partially be explained by the fact that use of the Report Builder was tracked at the practice level, and therefore has a higher likelihood of being accessed by someone in the practice. Still, less than 50% truly adopted the feature in the best case.

Factors Relating to Use

In both scenarios in this study, early explorers were much more likely to regularly utilize the features compared with those who waited to try the feature for the first time. Each month delay in trying a new feature was associated with a 2% drop in future utilization when adjusted for other factors, for both the Report Builder feature and the CPR. This effect has been noted in other areas of technology adoption, such as in the digital video recorder (DVR) market[43].

Other factors were less significant and varied based on the adoption scenario. Practice size was a significant factor relating to heavy use of the Report Builder feature, with larger practices more likely to utilize it more than 50% of the months in the study period. This observation is probably due to the greater staff resources of these practices.

Practice size was less of a factor in utilization of the CPR, with only the largest size (practice size >50) influencing utilization. The provider type was a more significant factor in CPR use; higher level providers (MDs, DOs) were significantly more likely to utilize the report than RNs and PAs. This is understandable since physicians generate the majority of the income for these practices and therefore can benefit more from operational changes. In addition, physicians are more likely to own the practices and have a financial stake in improvements that could come from these reports.

Factors Relating to Performance

The results relating to performance were varied. Use of these features was associated with better performance in three of the four metrics studied: days in accounts receivable, hold lag and work RVU. However, in the case of Report Builder, I was unable to detect a direct impact on performance through use of the feature when I compared pre- and post- feature performance. I was unable to perform a similar comparison in the CPR scenario because there was no pre-feature performance data available.

These results can be interpreted in a number of ways. It is possible that practices and providers that are more likely to want to view metrics are also more likely to be better performers on these metrics. I also did not study the totality of reporting features available to the providers; it is possible that the use of these features is correlated with other reporting usage, and these other reports provide the performance benefit.

Applicability to Health IT

This study looked at the use of reporting features to get a better understanding of the dynamics of health IT adoption. I attempted to broaden the applicability by choosing more than one feature to examine. However, this study was still limited to one vendor's implementation of a single type of functionality: reporting.

I used monthly use as the measure of regular utilization. Given the use of these features, monthly use was the most appropriate measure. Other features in future studies might have other measures of regular use.

A small set of operational and performance metrics was used to represent the practices' performance. The metrics that were used have generally been found by athenaHealth to be indicative of a high performing practice. This study found that those practices that utilized the features in this study generally performed better. However, it is still an open question as whether practices with good operational processes also deliver superior care.

Implications for Policy

In isolation, EHRs cannot solve the problems in the U.S. healthcare system. The increased EHR adoption that will likely result from the financial incentives in the ARRA can enable better care, but only if the providers and organizations use the data available to them to make operational and care delivery changes. This research indicates that a subset of practices will embrace the changes necessary, but a significant portion will not utilize functionality that can bring about improvement absent specific incentives to do so. The peak utilization of a feature will be limited by the applicability of the feature's capabilities and usability and will probably not be utilized by all of the practices that could benefit from it.

It is encouraging to see that "meaningful use" of an EHR must be demonstrated in order to receive incentive payments in the ARRA. What this term entails has not yet been defined, but it appears that quality reporting will be a component. Based upon the results of this study, health IT policy makers would be encouraged to use markers that incentivize physicians to make use of the wide range of beneficial features that EHRs contain.

Implications for Health IT Vendors

Health IT vendors sometimes assume that once training is complete and payment has been collected, the job is done. This research indicates that full adoption is not achieved among a significant portion of their clients. Customers cannot realize the full value of the health IT system without utilizing its features in a meaningful way, and customers who do not feel that they are getting significant value are more likely to change systems and provide negative reviews.

In addition, this research shows that adoption of functionality among new users and existing users has strong similarities. Therefore, it is important to have appropriate processes in place for introducing new users to the system's capabilities as well as showing existing users new capabilities. It cannot be assumed that existing users will adopt new functionality just because they are users of the current features, or that every member of a new practice will utilize existing functionality after some providers have undergone training.

Recommendations for Further Research

I am hopeful that this pilot study will inspire further research into the area of the dynamics of health IT adoption. An ideal study would look across multiple features relating directly to patient care. Study endpoints could include clinical measures relating to known best practices or patient outcomes. It would also be beneficial to look at multiple vendors' systems, in order to show how the usability of a specific system impacts the utilization. This study was limited to outpatient physicians with a demographic mix that does not entirely reflect that general makeup of the U.S. outpatient community. A study examining an outpatient physician population in line with the general population would be beneficial. Finally, other clinical settings should be explored. Inpatient, skilled nursing facilities and other care facilities should be examined in order to understand if these findings are applicable to these settings.

Study Limitations

There are a number of limitations of this research. First, this study population is not necessarily representative of the general outpatient provider population in a number of ways. This is a group that has self-selected to become athenaHealth clients. Therefore, they have already illustrated a willingness to adopt health IT. In addition, they are biased towards a practice distribution that matches athenaHealth's sales strategy, and is not a random sampling of outpatient practices. The demographics of this population do not necessarily match with the demographics of the outpatient provider population.

Second, I explicitly removed cost as a factor of adoption. This was intentional, as I was more interested in researching utilization of features rather than purchase of systems. However, these findings cannot be extended to understanding the adoption of health IT systems in which there is a cost involved.

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