

# The Diffusion and Value of Healthcare Information Technology

*Adoption rate of electronic health records  
consistent with similar IT in other industries*

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The United States spends more than \$1.6 trillion annually on healthcare, but almost no one would argue that we spend it efficiently. Despite these mammoth expenditures, Americans are not any healthier than citizens in most other developed nations.

Healthcare faces multiple problems, including high and rising expenditures, inconsistent quality, and gaps in care and access. Healthcare information technology, and especially complex electronic health records (EHRs), have been considered as possible partial solutions to those problems.

A number of prominent industries, including wholesaling and retailing, greatly increased productivity during the last decade largely due to IT transformation. RAND has examined

the use of IT in the healthcare industry, particularly regarding the adoption of EHRs, to see if a similar transformation is taking place and, how this transformation compares to those that occurred in other industries.

Our objective was to place our project into a broader context and provide a rigorous foundation for empirically and theoretically based projections of future EHR growth. We needed a theory that would help us predict—or at least bound—EHR diffusion in hospitals and ambulatory settings if nothing were changed. We also needed to go one step further and develop a basis for predicting, or bounding, changes in EHR diffusion as a function of potential new government policy. This output will be used and reported in future RAND work.



## Identifying historical diffusion curves

We searched the literature for candidate diffusion curves and identified more than two dozen. Some of the most useful for EHRs can be found in Teng, Grover and Guttler (2002), which lists the diffusion curves of 19 information technologies. The information was collected from 318 respondent firms in the United States from a mail sample of 900. The surveys asked the respondents, often CIOs, for implementation dates of the 19 technologies.<sup>1</sup> Using the survey responses, the authors constructed historical diffusion curves by adding up the number

of firms that reported having adopted a technology. Some of the diffusion curves are shown below. (Note that the time scales are different for the two graphs.)

The responses indicated that mainframes diffused much more slowly than PCs, and that e-mail, which began diffusing at roughly the same time, diffused much more slowly than PCs. Mainframes never diffused to 100 percent of the population, whereas PCs and e-mail eventually did. Computer Assisted Software Engineering (CASE) is a younger technology. Note that diffusion speed and ultimate saturation varies within IT innovation, even for the same sample of firms.

The tables illustrate not all innovations diffuse to 100 percent of the applicable population. There are usually very good reasons for this, including cost, technical needs and the technological progress of competing innovations. The median adoption period, including six IT innovations, is 25 years.

Because diffusion theory is well established, we used that theory to generate a prediction of future EHR diffusion and explain its past diffusion. We provide the lessons from a large literature survey.

## Using the literature to identify key drivers of diffusion

The diffusion literature is both vast and varied in its methodological approaches and interests. The books and articles we selected are more heavily weighted toward surveys or meta-analyses. They also are based on hundreds of diffusion articles and decades of research from a variety of disciplines. The literature can be organized in several categories:

- **Type of innovation**—Such as IT, agricultural, etc.
- **Industry**—Although healthcare is represented, many industries are studied and the important theoretical results apply across industries.
- **Academic discipline**—Such as sociology, economics, etc.
- **Level of analysis**—Refers to whether the study attempts to understand or predict the adoption behavior of individuals, organizations or entire industries. Individual adoption behavior, if it occurs within a firm, is often referred to as “intrafirm” diffusion.
- **Academic objective**—Such as prediction, description, etc.

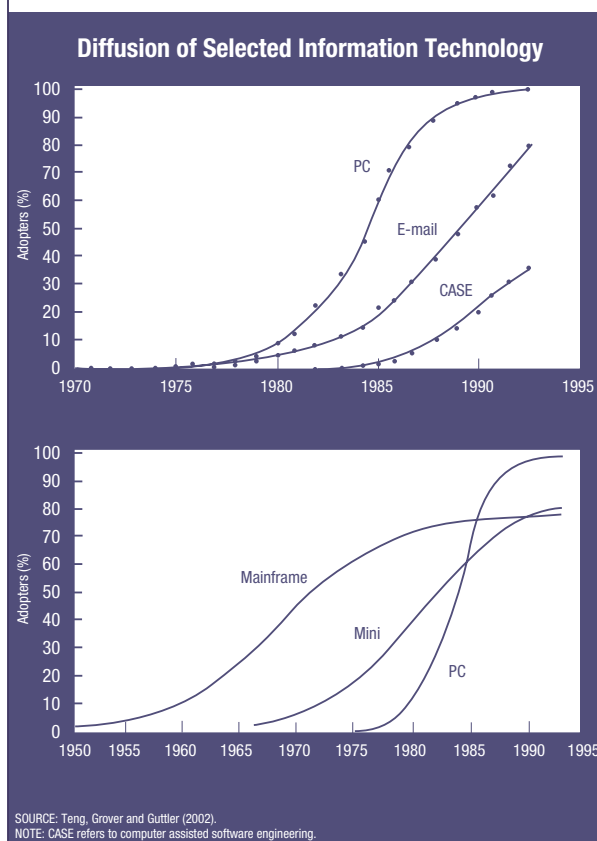
Despite the massive amount of work, most of it is descriptive. After collecting data on a historical diffusion process, variables are correlated with diffusion. Very little work has been performed that assists with ex-ante prediction of diffusion paths for specific technologies. This weakness in the literature appears to be increasingly well-recognized, and there are calls for further predictive work.

Partly because of this weakness, we decided to select and use important insights from several academic disciplines. We found it most useful to focus on a cross-product, cross-industry, cross-disciplinary, predictive framework.

## Key papers in healthcare IT diffusion

The theoretically strongest diffusion papers, crucial to building a predictive theory, are outside healthcare IT. However, the key papers in healthcare IT diffusion lead us to believe that the general diffusion theory is applicable to healthcare IT and to EHRs specifically. We review below only those few papers that build the bridge from diffusion theory to healthcare IT. Where healthcare appears to specifically depart from diffusion theory, we note it in the analysis.

England, Stewart and Walker (2000) place healthcare IT diffusion into Rogers' (1995) well-known diffusion framework. Their paper demonstrates that healthcare IT can be placed in a framework that is validated by a large body of existing work. This article is very much in the spirit of what we are trying to accomplish in providing a broader context for understanding healthcare IT diffusion. Although placing healthcare IT into a framework is not as good as testing



<sup>1</sup> This method of mail survey and rely-on-recall is standard for the literature. To construct the EHR diffusion curve, we relied on self-reported adoption data from Dorenfest. The advantage of Dorenfest is that the questions are asked every year, which presumably obtains more reliable answers for recent years.

healthcare IT adoption predictions in that framework, the authors are able to methodically assess variables that drive healthcare IT diffusion. The authors conclude that the observed “slow”<sup>2</sup> diffusion of healthcare IT is explainable, given the providers’ fragmented internal structure, immature status of strategic healthcare IT, constrained financial resources and complexity of the healthcare IT systems. The authors do not attempt to predict future healthcare IT diffusion or to suggest how government policy would change uptake quantitatively.

Anderson and Jay (1985) are important because their study validates a crucial point for our purposes. They find that informal communication networks, in this case physician networks, are vital to the diffusion process. This is consistent with Rogers’ (1995) framework in which informal communication networks are important to diffusion. Anderson and Jay find that network location has a significant effect on adoption independent of practice characteristics or the background of a physician.

Anderson and Jay also discovered that “epidemic effects” play a substantial role in physician adoption. Physicians talk to each other and social interaction is an independent driver of adoption—it is not merely associated with the “true” variables that drive adoption.

Epidemic effects are a classic externality. Their existence in this context suggests that some government intervention to promote adoption might be socially beneficial, depending on the state of diffusion.

### ***Generating a predicted EHR diffusion curve based on the broader diffusion literature***

To narrow the task of generating a predicted EHR diffusion curve, we focus on the level of analysis most important to our study: industry. This level is the most important because we are attempting to predict, or at least bound, total adoption of EHRs in the healthcare industry over time in the United States.

There are three approaches to producing a future industry diffusion curve for EHRs:

1. To create a predictive, statistical diffusion model based on empirical EHR adoption data disaggregated at least to the firm level, bolstered by solid similar empirical work from other industries.
2. To econometrically generate a predicted curve based on actual EHR uptake data to date in the form of statistical extrapolation.
3. An inductive approach that picks a diffusion curve from historically “similar” industries, where a tested theoretical model guides the selection.

The first approach is preferred on methodological grounds because it would clearly link changes in policy to underlying changes in variables that drive adoption, firm by firm. Unfortunately, the first approach is infeasible. We have concluded there is no robust predictive theory that would allow statistical estimation of EHR diffusion curves based on the multivariate model.<sup>3</sup> The second approach—pure extrapolation—is feasible but has been shown to be quite unreliable.<sup>4</sup>

We used the third methodology. We looked for (and for EHRs, constructed from scratch) historical diffusion curves, then used diffusion theory to pick the curve or family of curves that best predict diffusion of EHRs technology into the future. To select a diffusion curve, we needed to describe candidate curves easily. The literature has widely used an equation to describe industry diffusion curves (see, for example, Teng, Grover and Guttler, 2002, and Geroski, 1999). The rate of diffusion in an industry can be described as<sup>5</sup>

$$dN(t)/dt = (a + bN(t))[m - N(t)]$$

where

$N(t)$  is the proportion of the total potential adopters at time  $t$ ;

$a$  is the coefficient of “external” influence;

### ***Fast Facts***

RAND Corp. is a nonprofit research organization providing objective analysis and effective solutions that address the challenges facing the public and private sectors around the world

*The Diffusion and Value of Healthcare Information Technology*, published by RAND Corp. in April 2005, found:

- The electronic health record (EHR) adoption rate is consistent with other similar IT technologies in other industries, but initiatives should be put in place to ensure organizations effectively use EHRs
- Healthcare IT is a technology that requires broad policies to be effective
- Strong evidence suggests healthcare IT will complement other productivity features such as competition and deregulation
- The industry should continue to coordinate standards and push for initiatives to improve the chances for interoperability, especially within regional communities
- With the proper standards, the widespread use of healthcare IT in the U.S. healthcare system could save a substantial amount of lives and eventually hundreds of billions of dollars

$b$  is the coefficient of “internal” influence or “imitation;” and

$m$  is the proportion of the potential adopters that will ultimately adopt (note this may be less than 100 percent).<sup>6</sup>

<sup>3</sup> What would be required from a dataset to populate and test such a model? As a starting point, we would suggest longitudinal panel data of a broad sample of health providers, including their EHR adoption dates, size, for-profit status, the level of competition in each local market, products available with features and prices, government policies including subsidies and taxes, and expectations regarding future prices and features. Data on hospital marginal costs, economies of scope and learning curves would also be helpful. Creating such a dataset is potentially feasible but has not been done yet for EHRs.

<sup>4</sup> This method generates diffusion curves from early healthcare IT adoption data alone. It is possible to run a regression that uses existing data to generate a “predicted” curve. It has been shown that generating diffusion curves from early adoption data is not statistically sound (Sultan, Farley and Lehmann, 1990) because there are not enough data on which to base a reliable estimate and, perhaps more seriously, they are almost atheoretical in their construction. Thus, we will avoid relying on such estimates. Further, the adoption data are likely autocorrelated (Karshenas and Stoneman, in Stoneman 1995). While there are econometric fixes for the autocorrelation problem, they further reduce effective sample size, which exacerbates the reliability problem.

<sup>5</sup> A more general form of the equation that replaces the term  $a + bN(t)$  with  $g(t)$  has been used as well, but it sheds little additional light on the exposition and is omitted.

<sup>6</sup> This is a differential equation whose solution is a logistic curve characterized by a long equation and is omitted for brevity.

<sup>2</sup> See, for example, Dong and Saha (1998).

The external influence parameter (a) has been interpreted as the influence of change agents such as vendors, government publicity and consultants. The internal influence parameter (b) could represent the influence of other adopters on the rate of adoption—notice that it is multiplied by the proportion of current adopters,  $m - N(t)$ . This is known in some contexts as an epidemic effect, because it is mathematically and conceptually the same as contagion models in biology, in which epidemics spread through contact among individuals. The proportion of eventual adopters is influenced by the specialization, usefulness and speed with which an innovation overtakes it.

When this equation is fit to historical adoption curves, the statistical correlation (R<sup>2</sup>) often will exceed 99 percent (see, for example, Teng, Grover and Guttler, 2002).<sup>7</sup> Many studies have shown that the diffusion equation and its cousins fit diffusion data in many industries very well (Mansfield, 1961; Romeo, 1975; Sultan, Farley and Lehmann, 1990; Wang and Kettinger, 1995).

### **Selecting a healthcare IT diffusion curve**

In this section, we select one historical diffusion curve as a basis for predicting healthcare IT adoption, relying on the theory and evidence presented in the previous section.

It is important to note that diffusion at the industry level does not connect automatically or mechanically to the data that we collect. To select a diffusion curve, industry-level information is needed to find parameters (a), (b) and (m) to write down the curve

$$dN(t)/dt = (a + bN(t))[m - N(t)].$$

However, what we collected is detailed qualitative site-specific information about how key informants inside their respective organizations viewed relative advantage, complexity, network externalities and so on. Therefore, the data collected are at a different level (key respondents instead of industry) and of a different kind (characteristics instead of (a, b, m)).

We are aware of only one paper that attempts to take characteristics from diffusion theory and use them to suggest the rate and ultimate level of diffusion (a, b, m) in an industry. We use this paper for our analysis.

Teng, Grover and Guttler (2002) study 19 IT applications in a survey that was sent to 900 U.S. companies and received responses from 318 firms (this is considered a good response rate in the diffusion literature).<sup>8</sup> They fit the curves to several models, finding that the mixed influence model provided the best fit in more technologies than competing models.

***“EHRs have high levels of relative advantage for most, but not all, practitioners. Value is relatively less to distant sites, and we hypothesize that EHRs might not diffuse completely to those sites, especially if they are poorly funded.”***

All the models had very high levels of fit—often more than 99 percent. The 19 regressions yield 19 estimates of (a, b, m), each corresponding to one IT innovation’s diffusion. Because (a) is close to zero in virtually every regression, they omit (a) and consider the pairs (b, m). They subjected the 19 pairs to a factor analysis to see how the technologies cluster. The vertical axis is (m), the ultimate saturation, and the horizontal axis is (b), the coefficient of imitation, which is proportional to the speed of diffusion (roughly, the slope of the diffusion curve). There are similarities within the groups that appear to be explained using diffusion theory.

According to the authors’ analysis, an IT innovation will tend to achieve higher levels of saturation (high m) if it has:

- High relative advantage
- Less specialized appeal/greater mass appeal
- High compatibility with user work processes
- Low complexity

An innovation will achieve faster diffusion if:

- It is a device, not a system
- Has a low level of network externalities

We can now apply our assessment of EHRs with the criteria immediately above. First, we consider saturation level (m). EHRs have high levels of relative advantage for most, but not all, practitioners. Value is relatively less to distant sites, and we hypothesize that EHRs might not diffuse completely to those sites, especially if they are poorly funded. EHRs have moderate compatibility and high complexity. On balance, this implies a moderate-to-high level of ultimate saturation.

With respect to the rate of diffusion, EHRs are certainly systems, not devices, and have significant network externalities. Taken together, this suggests a relatively slow rate of diffusion as compared to other IT innovations.

Armed with this information, we can select a candidate curve for EHRs.

It appears most likely that EHRs fall in Cluster 2, as we might expect a large but not maximal proportion of eventual adopters and a slow rate of diffusion. Simply inspecting the clusters, it appears

<sup>7</sup> Other models that use a different functional form for the term  $a + bN(t)$  generate almost equally high R<sup>2</sup>.

<sup>8</sup> There is some evidence that mail surveys have not proven to be reliable in healthcare IT. Ash et al. (2004) found response bias in their study of CPOE adoption.

that EHRs are a relatively good fit with Cluster 2 technologies and a relatively poor fit with technologies in other clusters. For example, EHRs require coordination and high levels of data integration, as do large-scale relational databases (LSRDs) included in Cluster 2.

On the other hand, EHRs are much more complex to implement than spreadsheet programs, included in Cluster 4. (Note

that spreadsheets diffused rapidly to 100 percent of the corporate population.) We looked for a specific IT innovation to use as an EHR comparison among Cluster 2 IT innovations. These innovations included fourth generation languages (4GL), mainframes, minicomputers and LSRDs. EHRs do not appear to be like a fourth generation language, so we thought they were less likely candidates. Mainframes are more than 50 years old and minicomputers are more than 35 years old, and so their ages may make them less of a close fit with EHR diffusion dynamics. On the other hand, LSRDs seem to be more recent and share characteristics with EHRs. Both are complex and relational, and contain large amounts of data.

In light of these results, it seems that EHR diffusion has been “slow” more with respect to high expectations of innovators than with respect to historical rates of diffusion across numerous technologies, including recent IT innovations. In addition, to the extent that it has been slow, it is explainable within classic diffusion theory: Historically, complex systems diffuse more slowly, and systems characterized by externalities diffuse more slowly. EHRs have both of these qualities.

Considering both theory and historical information, it may not be realistic to expect EHRs to diffuse across 100 percent of potential adopters without government intervention.

### Diffusion, productivity and how both affect policy decisions

It is important to remember that diffusion does not necessarily lead to productivity, particularly in the short term. These changes may take a decade or more to become apparent. What is needed is evidence regarding long-term changes and productivity gains, and a theory of the drivers of IT benefits.

Such evidence exists in other industries. Some industries, such as telecommunications and securities trading, have undergone IT transformation and obtained major productivity benefits, resulting in higher profits, higher wages and, especially, higher consumer surplus. Other industries, such as hotels and retail banking, have made the IT investment but have not reaped the benefits.

Therefore, IT-led productivity gains vary not only by industry, but also by time period and specific IT application. It is notable that more than 50 percent of hotel staff are maids and janitors, who are relatively unaffected by IT. It is interesting to note that healthcare organizations, especially hospitals, have substantial hotel-like functions and could likely have some of the same problems in leveraging IT for a segment of their employees.

Based on this examination, RAND

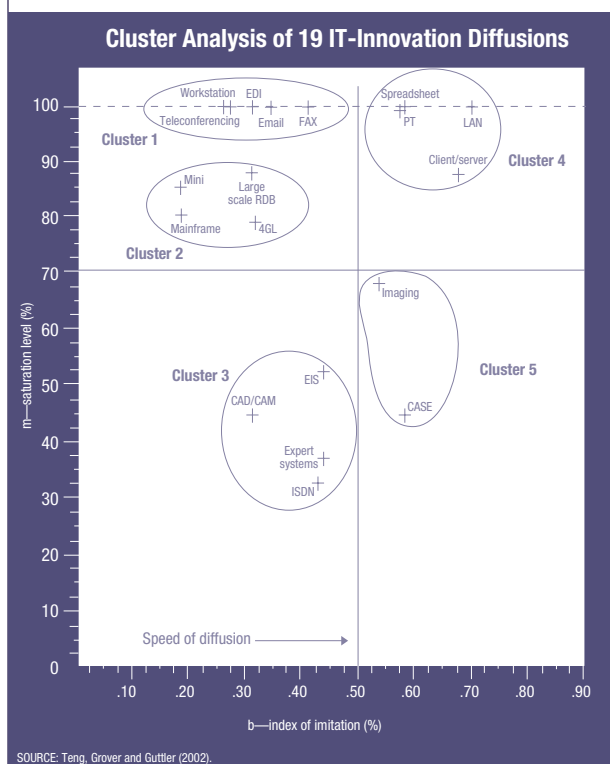
recommends developing policy and solutions in these broad policy avenues:

#### 1. Coordinate standards immediately

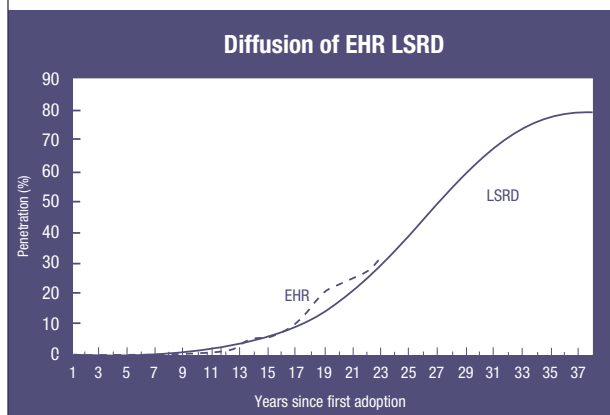
The industry should continue to coordinate standards and push for initiatives that improve the chances for interoperability, especially within regional communities. Standards should be improved without reducing competition among EHR suppliers.

#### 2. Work to improve quality measurement

The benefits of improving quality measurement are twofold: First, improving quality measurement will help to overcome the healthcare market failure of inadequately recognizing quality. This will spur the adoption of quality-improving innovation, including EHRs. Second, there is a feedback loop: Adoption itself will reduce this market failure because EHRs hold the promise of improving quality measurement, largely by automating an otherwise dauntingly labor-intensive process of quality management. This difficulty in measuring and competing on quality is arguably the most important problem in healthcare, and EHRs could be an important part of the solution.



SOURCE: Teng, Grover and Guttler (2002).





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*“Through the widespread use of healthcare IT, we believe that the U.S. healthcare system could a substantial amount of lives and eventually hundreds of billions of dollars.”*

### 3. Recognize healthcare IT requires complementary investments.

Other industries have shown that IT is much more effective when combined with vigorous competition and deregulation. Complex technologies such as EHRs are definitely not stand-alone or plug-and-play types of benefits. If (and only if) used appropriately, IT can deliver dramatic changes in the overall delivery of care that could radically improve quality and lower the cost.

### RAND study set for fall release

For the past two years, RAND has been studying the U.S. healthcare system, and we will release our findings this fall.

Through the widespread use of healthcare IT, we believe that the U.S. healthcare system could save a substantial amount of lives and eventually hundreds of billions of dollars. Cost savings would stem from several sources, including CPOE, increased hospital and physician practice efficiencies, reduced length of hospital stay and administrative costs, and optimized drug utilization. Additionally, IT-enabled preventive care and chronic disease management programs offer savings by controlling acute episodes and reducing physician and hospital visits. 

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