

# **Coordinating quality care: A policy model to simulate adoption of electronic health records**

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## **Abstract**

This article reports on a theoretical simulation model to investigate effects from policy interventions in the adoption of electronic health records among hospitals, physicians, and patients. The project draws on established system dynamics diffusion theories and provides a conceptual framework to develop and test interventions to promote adoption of electronic health records. Using data from the Greater Capital Region, Northern New York State, the findings from the simulation experiments suggests that there is no single right intervention but a combination of measures to promote the use of electronic health records not only on the provider side but also among patients.

*Keywords: diffusion, electronic health records, policy interventions, system dynamics*

## **Introduction**

With the increasing cost of the U.S. healthcare system, which is approximately 16 percent of GDP, government and stakeholders are looking for way to reduce cost while increasing quality care. It is suggested that one of the measures to address the escalating cost facing the U.S. healthcare system is to use electronic health records (HMFA 2006). Using electronic health records not only affects cost but also reduces to error rate in patients treatments. A 2006 report from the Institute of Medicine (IOM) of the National Academics found that medication errors harm at least 1.5 million people every year accounting for \$3.5 billion per year in extra medical costs to treat drug-related injuries.

An electronic health record (EHR) refers to an individual patient's medical record in digital format. Electronic health record systems co-ordinate the storage and retrieval of individual records with the aid of computers. EHRs are usually accessed on a computer, often over a network. It may be made up of electronic medical records (EMRs) from many locations and/or sources. Among the many forms of data often included in EMRs are patient demographics, medical history, medicine and allergy lists (including immunization status), laboratory test results, radiology images, billing records and advanced directives ([http://en.wikipedia.org/wiki/Electronic\\_health\\_record](http://en.wikipedia.org/wiki/Electronic_health_record)).

Increasing the adoption and use of electronic health records (EHR) could address two of the most critical challenges facing the U.S, healthcare system: enhancing quality of care and controlling costs. The result of an increased adoption of EHRs and other health information technology in the U.S. could be to save lives and \$162 billion annually, according to a new study by the RAND Corp (Hillestad 2005). Potential cost savings include increased efficiencies (\$77 billion), reduced prescription errors (\$4 billion) and improved health quality via prevention and

disease management (\$81 billion). While the cost advantages for EHR look very compelling, the adoption rate in the U.S. is rather low due to a variety of factors. Explanations range from macro-level systemic factors (such as the lack of enabling healthcare policy at the national level or the inability to achieve broad information standards) to micro-level individual barriers (such as perceived complexity and resistance from physicians) (Vishwanath 2007).

A number of research studies have addressed the adoption of EHR, using methodologies that vary considerably, for example, quantitative surveys, (Weiner 1999; O'Connell 2004) observations, (Patterson 2004) quality focus groups, (Lyons 2005; Wallis 2006) and ethnographic studies (Saleem 2005). In addition to the variety of research methodologies, the previous mentioned studies focus on different types of barriers influencing the adoption of EHR. Some focus on human factors such as training and support (Patterson 2004); software related barriers (Saleem 2005) or the lack of perceived ease of use and usefulness, as potential adoption barriers (cf. Lyons 2005; Wallis 2006).

The broad spectrum of research approaches to help understand what drives the adoption of EHR, with different explanations and disparate foci make it difficult for policy maker to recognize the leverage of individual policies. Vishwanath (2007) tries to fill the gap and presents a comprehensive, empirically based conceptual model of the barriers to EHR adoption among physicians. The aim of the study is to evaluate a framework that allows policy makers to better judge the intensity of the different barriers influencing EHR adoption and test suitable interventions. While Vishwanath's study is based on concept mapping, a methodology that has been compared to astronomy in its ability to map and represent both the big pictures as well as the small detail, it does not allow to quantify and measure the result of different policy interventions influencing the adoption of EHR over time.

While previous studies provide valuable insights and explanations on a number of individual barriers for EHR adoption, little attention has been given to the interrelated nature of policy interventions and the ability to clearly measure and understand the component effect of each barrier. The goal of this paper is to extend previous research by applying the system dynamics methodology to help understand the effects of different policies in the adoption and diffusion of EHR. System dynamics models have been successfully applied in a variety of settings to gain insights into the mechanics of diffusion (cf. Morecroft 1985; Maier 1998; Milling 2002).

In the following section we develop a basic simulation model, designed to capture the dynamic nature of policy interventions, which affect the adoption of EHR. Our study is aimed at capturing key interactions in the adoption of EHR for hospitals, physicians, and patients. While our aim is to conceptualize a simulation model, which is able to replicate ‘real-world-behavior’, some structural components in our model are represented in aggregated form. Nevertheless, our dynamic non-linear model provides the following advantages over traditional linear models.

*First*, the simulation model captures the dynamic characteristics of policy interventions that can help to increase the adoption rate for EHR. Although the representation of the system, along with the causes influencing EHR adoption is highly aggregated, the model provides insight into the dynamic behavior of organizations and individuals with respect to the use of EHR. *Second*, the model can be used to simulate and test different policies that might influence the adoption of EHR and, thus, provide insights into the effectiveness of selected policies.

## Context and Boundary of Study

The adoption rate of EHR can be attributed to a variety of factors from the systemic macro-level to micro-level individual barriers among physicians and patients. On the micro-level, barrier for EHR adoption are perceived benefits, for example, ‘improved access to medical record information’, ‘improved drug refill capabilities’ or ‘improved claim submission process’ (Gans et al. 2005). On the macro-level, it is suggested (Vishwanath 2007; Middleton 2005) that the major factors influencing adoption of EHR consist of a combination of awareness campaign, educational interventions and training, as well as financial incentives, along with enabling healthcare policies and national standards for security and data exchange. For the purpose of our model, we chose the following policy interventions, which, individual or in combination, can affect the adoption of EHR on the macro-level. *First*, ‘awareness’, which includes activities, for example, to promote information about existing standards, functionality of EHR, and patients’ benefits. *Second*, the policy intervention ‘education and training’ entails measures to overcome learning barriers that EHR present for healthcare professionals and healthcare management. The *third* high-level policy intervention we include in our model is ‘financial incentives’, which aims to stimulate the EHR market through reimbursement reforms and capital availability.

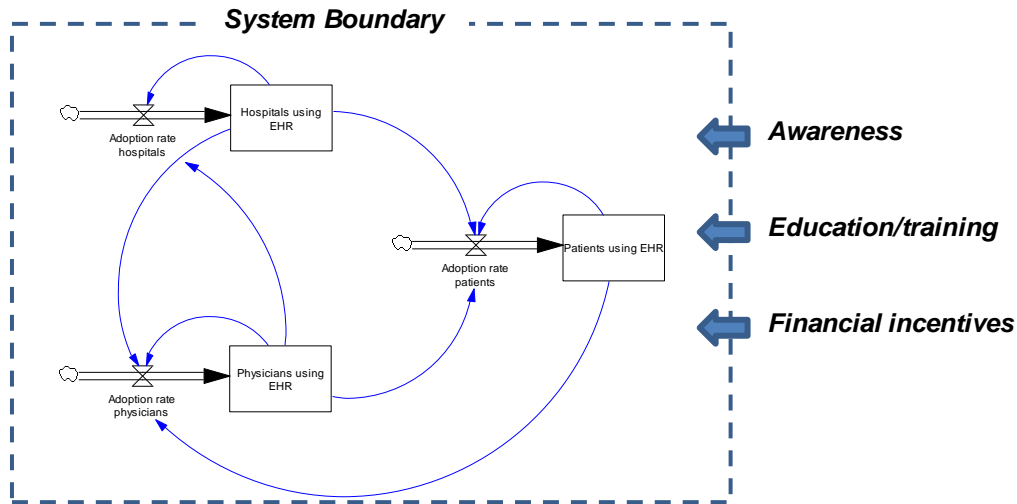


Fig. 1. System Boundary of Model and Policy Levers

Figure 1 shows the aggregated view of the simulation model. We draw the system boundary around the three stocks ‘hospitals’, ‘physicians’, and ‘patients’ to captures how policy interventions affect the adoption of EHR among the key entities using medical records. In the absence of empirical studies looking at EHR adoption among payers, e.g. regional or state health plan associations, we exclude this entity from the model.

The model is also generic and aggregated with respect to regional issues in promoting EHR adoption. There are currently a number of state-wide initiatives unfolding to promote a common platform to facilitate the exchange of electronic patient records. In New York State, for example, HIXNY (Healthcare Information Xchange of NY) a not-for-profit organization is pursuing an initiative to accelerate the adoption of health information technology across health care organizations, patients, and communities. Given the expected benefits associated with EHR, we can assume that other organizations across the U.S. are also pursuing similar initiative like HIXNY. Another approach to promote the adoption of EHR is currently undertaken by Google.

Google Health defines itself as a ‘*personal health information centralization service (sometimes known as personal health record services)*’ allowing Google users to volunteer their health records – either manually or by logging into their accounts at partnered health services providers – into the Google Health system, thereby merging potentially separate health records into one centralized Google Health profile. Volunteered information can include ‘health conditions, medications, allergies, and lab results’. Once entered, Google Health uses the information to provide the user with a merged health record, information on conditions, and possible interactions between drugs, conditions, and allergies. Google’s Health system is going beyond state boundaries enabling its users to move health information across the U.S. without the need to align the electronic record to a platform or technology.

As stated earlier, the objective of this paper is to evaluate how policy interventions, either initiated by the federal government or organizations, such as HIXNY, affect the adoption of EHR. To assess how policy interventions affect the adoption of EHR, we propose the following set of dynamic conditions.

*I. Physicians with higher levels of awareness for the benefits of EHR will have a higher likelihood to adopt.*

A recent study by Davidson and Heslinga (2007) contends that physicians in their sample were aware of EHRs but did not made the decision to adopt for concerns that costs would be too high or for legacy issues with the existing practice management system. Furthermore, uncertainty about vendor selection was also factor to inhibit the adoption of EHR. Our proposition contradicts the study conducted by Davidson and Heslinga and we will use the simulation model to confirm or reject or dynamic hypothesis.

*II. Learning-related activities will affect the assimilation of EHR among hospitals, physicians, and patients.*

Reardon and Davidson (2007) investigate the assimilation of EHR and conclude that learning and related knowledge was positively associated with small physicians' practices' stage of EHR adoption. The study, however, does not include how learning can affect the adoption of EHR within a hospital setting or patients. Furthermore, the study does not consider feedback effects when one entity, e.g. patients or hospitals, with better knowledge of EHR technology can influence another entity where knowledge may be lower.

*III. Lack of financial incentives will negatively influence the adoption rate of EHR in hospitals and physicians offices.*

It is a common belief that financial incentives can promote the adoption of EHR. However, to date there have been no studies that present a comprehensive view on how financial incentives will affect the adoption rate across physicians, hospitals, and patients. While existing studies (cf. Gans et al. 2005; Reardon and Davidson 2007; Vishwanath 2007) empirically identify financial incentives as one of the barriers to adopting an EHR system, little is known about how changes in financial incentives will affect the adoption rate.

These dynamic hypotheses will be examined using the system dynamics method. Substantive interpretation of testing the intervention policies with the simulation model will be discussed.

## **Model Conceptualization**

The low level of EHR adoption is influenced by many factors and range from, for example, cost of hard- and software, lack of financial incentives, and implementation issues (Reardon and



Davidson 2007). While these factors help explain the low level for EHR adoption, they do not explain how policy interventions may change the adoption and use of EHR. Thus, the ability to use a simulation model may help policy makers design effective interventions and help explain the variations in EHR assimilation among the macro-sized organizations. To investigate organizational factors influencing the adoption of EHR, we propose a system structure, which at its core resembles a Bass-type diffusion model (Sterman 2000).

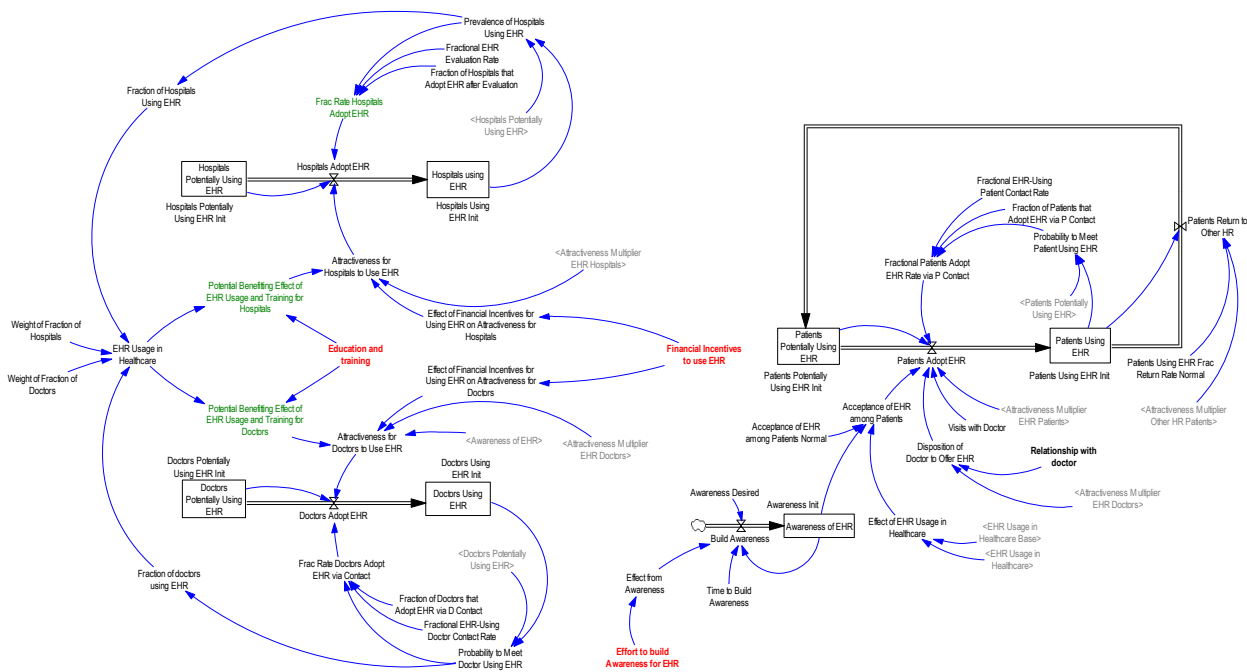


Fig. 2. Overview Model Structure

As outlined on Fig.1, the model consists of three policy levers and a stock-flow structure to capture the adoption rate among key entities using or promoting EHR. The central construct in our model is the co-flow structure, where the ratio of EHR use in hospitals and physician offices will affect the adoption rate. We stay close to the Bass diffusion model and conceptualize a generic word-of-mouth (WOM) structure for physicians and patients. In absence of empirical

studies, we conceptualize the adoption rate for EHR in hospitals and physicians as a function of attractiveness, an effect from financial incentives, and education and training. Our operational definition of ‘attractiveness’ is based on the notion that a unit attractiveness is suggested for organizations who don't have any external reference, but just feel the need for process and quality improvement and therefore are attracted adopting EHR. Thus the formulation for attractiveness of EHR depend both on the pressure the organization faces to adopt quality improvement programs because of efficiency needs, and the information the organization is getting from market about the attractiveness of the technology.

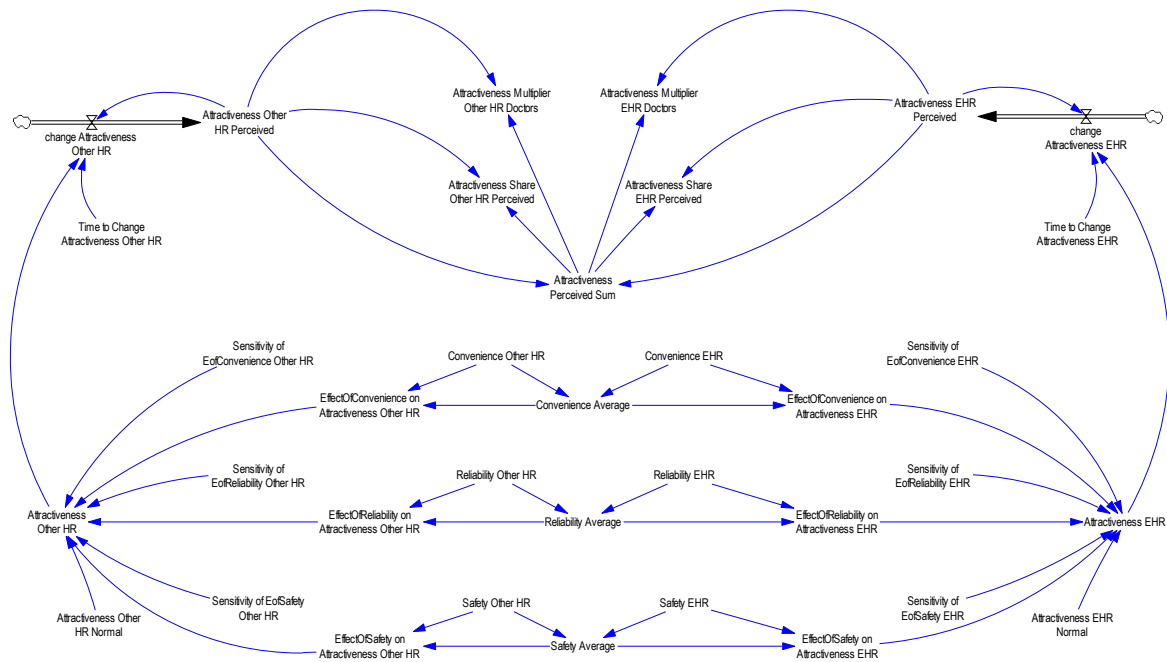


Fig. 3. Symmetric Structure for Attractiveness to use EHR

Figure 3 depicts the construct how we formulate the attractiveness for using EHR. In using such a formulation, we assume a symmetric structure of efficiency, reliability, and safety

between the traditional, paper-based process, and using electronic medical records. The same construct is used for hospitals and patients, assuming that EHR have a similar symmetric attractiveness structure. The initial values for ‘convenience EHR’, ‘reliability EHR’, and ‘safety EHR’ is set to 1, while the values for the paper-based process is set to 0.9, 0.5, and 0.5, considering lower reliability and safety but only a marginally lower value for convenience (0.9).

We formulate the construct ‘awareness’ to capture that if physicians are aware of EHRs, they will change their attitude towards the benefits for using electronic records and subsequently adopt. However, Davidson and Heslinga (2007) conclude that although physicians are aware of EHR they do not always adopt for concerns of costs would be too high or reluctance to replace an existing practice management system. Thus, our construct ‘attractiveness for doctors to use EHR’ does need to be viewed in the broader context of the simulation model.

Another construct in our model is how education and training may affect the adoption of EHR in hospitals and among physicians. Reardon and Davidson (2007) conclude that learning and related knowledge are positively associated with higher levels of EHR assimilation. To capture this association we theorize that efforts in education and training will increase the expected utility for EHR (or potential benefits) amplified by the ratio of EHR penetration. Thus, higher usage levels (ratio of EHR use) will increase the potential benefits, which will affect the adoption rate.

The construct of the patients’ adoption rate is based on a number of key assumptions. *First*, we assume that if the fraction of physicians using EHR increases, it will improve the relationship with a physician, given that patients will experience more quality care. *Second*, awareness for EHR may affect how patients perceive the social factors (e.g. privacy, digitization

of personal information) using medical records. *Third*, we assume that a stronger relationship with a physician may change a patient’s attitude towards adoption and use of EHR.

### ***Base Line***

In calibrating the model we use the limited data, which is publically available and use reference values from the Greater Capital Region, Northern New York State. While we are able to use data from an empirical study, which measured HIT (health information) adoption with a rather large sample of 3983 hospitals in the U.S. (Agarwal 2005) we have not been able to find time-series data about the adoption rate among physicians. In the absence of empirical data to map the adoption of EHR in physician offices over time, we use aggregated information, reporting that the adoption has increased in recent years but represents less than 25% of physician practices in the U.S. (cf. Menachemi 2006; Simon 2007).

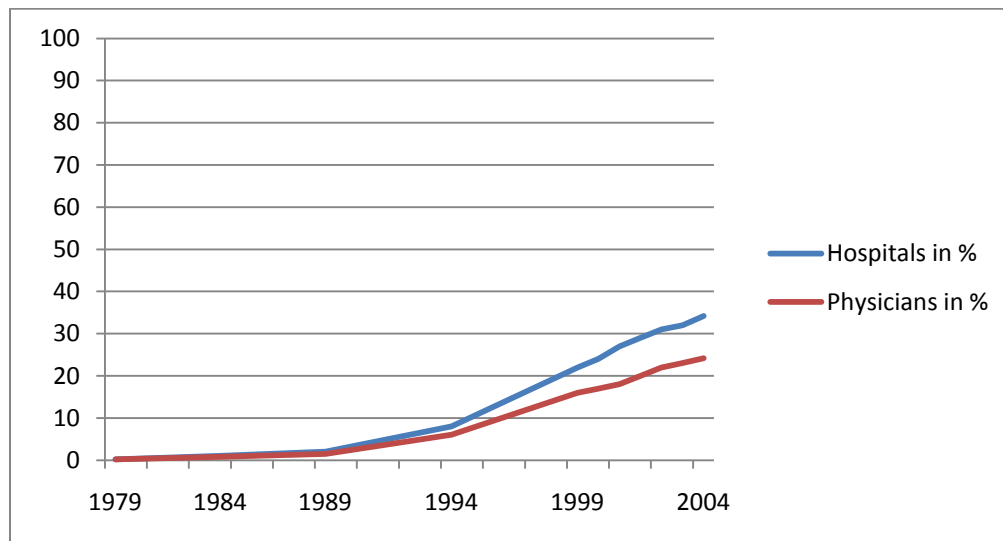


Fig. 4. Adoption of EHR in the U.S. in Percent

Figure 4 depicts the adoption rate of EHR based on available data. While the data series for hospitals is based on an empirical study, we only had one data point (as stated above) for physicians and approximated the slope on the assumption that the adoption rate followed the same trajectory as the hospitals. Furthermore, in absence of time-series data on the EHR adoption for individual states in the U.S., we generalize and assume to find the same patterns across different states. Thus, we will use the time-series data shown on Fig. 4 as reference mode to calibrate our model. The initial value for the three stocks is based on market data (<http://www.statehealthfacts.org>) reflecting the geographical region (as stated above) we want to capture with our model: (1) hospitals: 48 (including health centers), (2) physicians: 4000, (3) patients: 1.4 million.

Richardson and Pugh (1981) contend that one can have increased confidence in the insights that derive from the model if the reference environment can be replicated. Sterman (2000) offers 12 tests, examining models on both structural and behavioral grounds.

Other tests focus on collaborative model building projects that include both modelers and model users. Richardson and Pugh (1981) divide confidence-building tests into those that test for suitability and those that test for consistency. Suitability tests determine whether the model is appropriate for the problem it addresses, while consistency tests examine whether the model is consistent with the particular aspect of reality it attempts to capture.

In validating our model, we performed direct structure tests (Forrester and Senge 1980) and compared our model with generalized knowledge about the system and confirmed the structural dimension and constructs in our model, with interviews of experts in the field. For dimensional consistency and extreme condition tests, we used VENSIM to a) ensure that the units of all variables are consistent and b) to see how the model responds when changing

parameters to extreme values. In order to perform parameter confirmation test, we searched the literature for available knowledge about the real system. For parameters for which we did not have empirical values we used a ‘best-guess’ approximation, tested the value of our assumptions using VENSIM’s sensitivity analysis, and adjusted parameters to replicate the time series data on Fig. 4. However, because most of the variables used in the model are hard to measure, calibrating against real data does not mean the model is valid.

### Exercising the Model

In this section we show a number of graphs comparing the base line simulation against policy interventions to stimulate the use of EHR. Figure 5 shows the base line to approximate the sparse data we were able to retrieve. For we did not have time-series data to calibrate the model, calibration is more a visual comparison, mapping the model to the data reported in the literature.

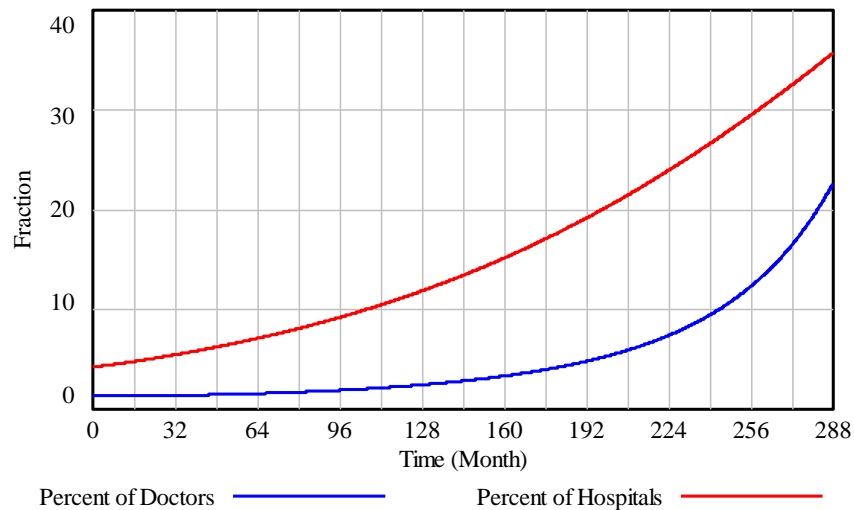


Fig. 5. Base Line Model Behavior

As stated earlier, the parameters in the model, where available, reflect the EHR assimilation in the Greater Capital Region and Northern New York. The initial value for the stocks ‘doctors’ is

set to 50 and for ‘hospital’ to 2, assuming that early adopters have used EHR at the time of interception. We adjusted the fractional adoption rates for the three stocks to map the base line of the model with the data as shown on Fig. 3.

The parameter values for the policy levers are set as following: (1) *education and training* to 0.5 (on a scale from 0 – 1) reflecting a broader approach to spread learning-related activities for EHR across hospitals and physicians. (2) *Financial incentives to use EHR* is set to 0.2, indicating that government is not doing enough to provide financial aid to deploy the required systems. (3) The initial value for ‘*effort to build awareness for EHR*’ is 0.5, assuming moderate effort from the Department of Health and insurance companies (payers) to promote the benefits for using EHR.

### ***Policy Experiment: Awareness***

In the first policy test, we increase the effort to build awareness by 20 percent, while keeping financial incentives and educational effort unchanged. Thus, we assume that additional resources would be used to support an EHR awareness campaign targeted at doctors and patients. An awareness campaign targeted at doctors and patients would help to increase the number of patients using EHR (shown on Fig. 7) through the direct effect from learning about the benefits and an indirect effect from a higher EHR usage in hospitals and among physicians.

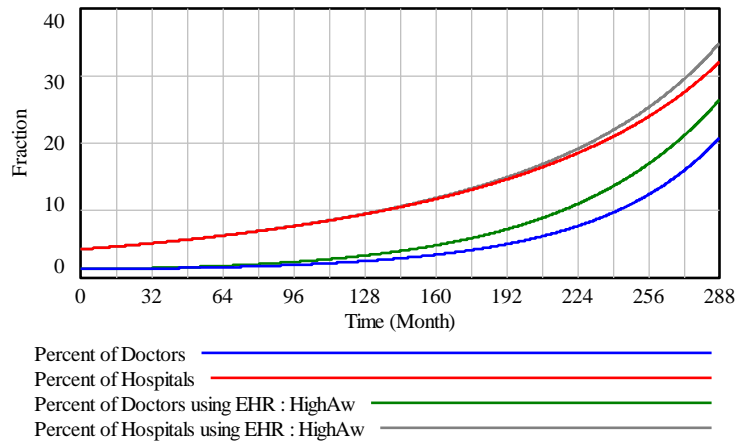


Fig. 6. Model Behavior with 20 Percent Increase in Awareness

While the percentage of doctors is increasing by about 8 points, hospitals using EHR is only growing by about 3 percent points, as shown on Fig. 6. We attribute this to the model construct, where we link ‘awareness of EHR’ to the variable ‘attractiveness for doctors to use EHR’ but don’t conceptualize a connection from ‘awareness’ to hospitals. Hospitals are rather complex organizations with a large number of stakeholders and we theorize that they are hard to reach through traditional awareness campaigns.

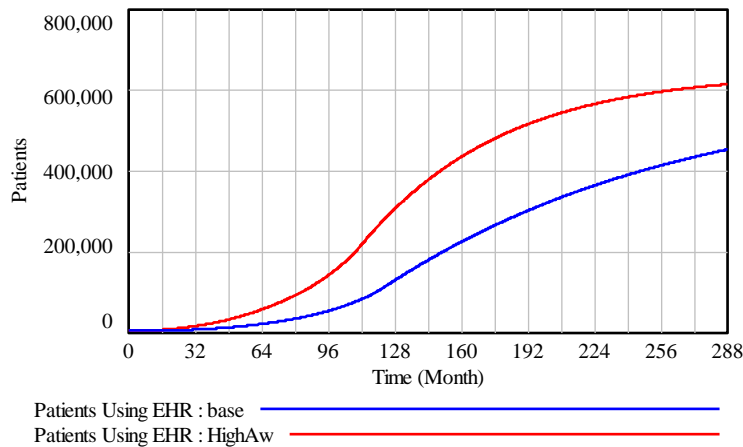


Fig. 7. User Base when Increasing Awareness



On the patients side, an awareness campaign will help to increase the user base but only if the measures are also targeted at doctors. As such, the model structure assumes that policies aimed at increasing awareness levels will have a board approach to include physicians and patients at the same time.

***Policy Experiment: Financial Incentives***

In this simulation experiment, we increase the level of financial incentives by 20 percent, keeping education and awareness on the base level value.

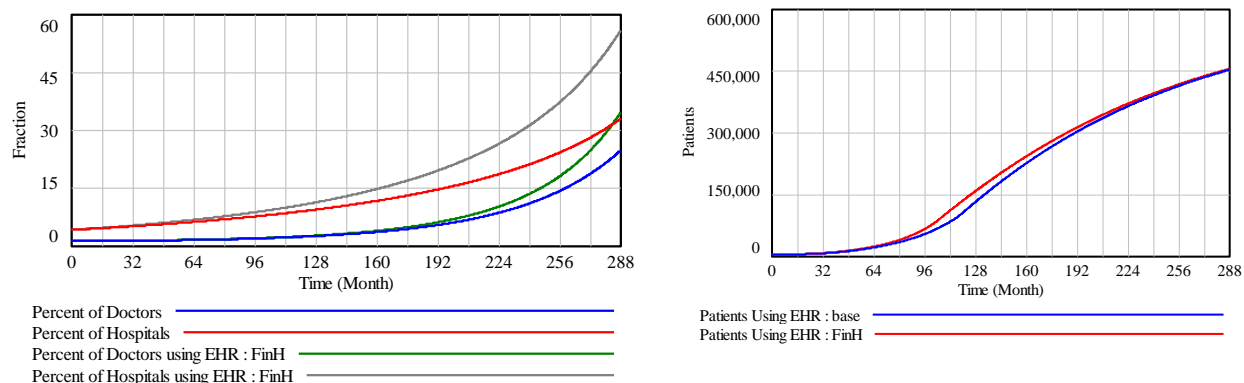


Fig. 8 a&b. Model Behavior with 20 Percent Increase in Financial Incentives

As shown on Fig. 8 a, a 20 percent increase in financial incentives results in a 10 percent increase in doctors using EHR and 23 percent for hospitals. The slow increase from this policy change is based on how we conceptualized the non-linear effect of financial incentives in the model. It is suggested that existing paper-based patient records must be converted to electronic records, as such, the greater the base of records, the greater the cost and effort to convert the base. Hospitals have more resources to convert paper-based records than physicians so the effect

from financial incentives is conceptualized accordingly. While this policy will help to increase the EHR adoption in hospitals and physicians, the change on the patient side is marginal.

***Policy Experiment: Education and Training***

A 20 percent increase in education and training results in the model behavior shown on Fig. 9 a&b. The effect from this intervention suggests that education and training have a higher yield at hospitals than for physicians. We attribute this behavior to the reinforcing loop ‘fraction of hospitals using EHR’ which suggests that if the fraction of hospitals increase the potential benefits for education and training is proportionally increasing as well.

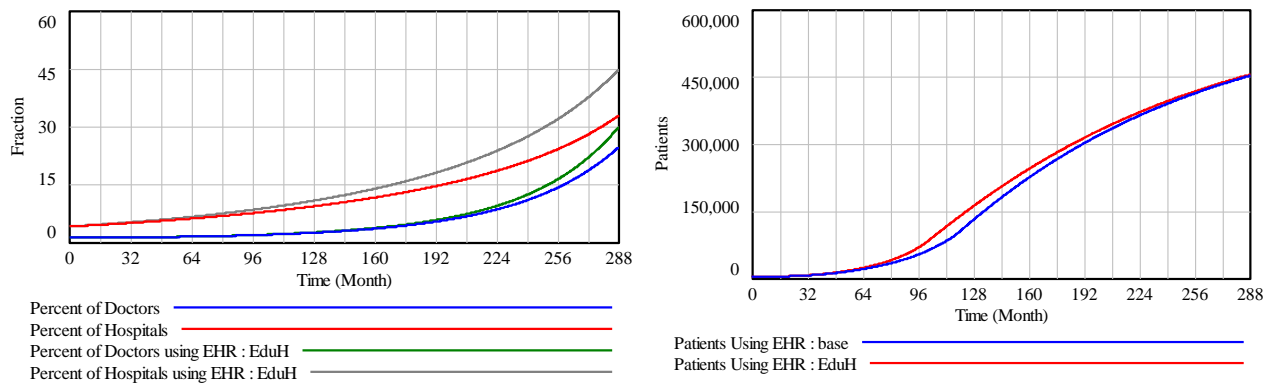


Fig. 9 a&b. Model Behavior with 20 Percent Increase in Education and Training

Furthermore, we conceptualize the non-linear functions ‘effect from training’ to capture the idea that education and training differs from a hospital environment to a physician’s office. The effect from education and training is marginal for patients, with the same underlying structural dimension as for the financial incentives. As such, it does not confirm our second hypothesis that *Learning-related activities will affect the assimilation of EHR among hospitals, physicians, and*

*patients*. While this intervention affects the adoption of EHR among hospitals and physicians, it does not influence patients to the same extent.

## **Discussion**

In this study, we drew on diffusion theories to investigate a persistent and troublesome problem, the adoption of EHR among hospitals, physicians, and patients. Our study highlights the need for policy interventions for promoting EHR adoption. Although our model is highly aggregated, it helps policy makers to understand that there is no single right intervention but a combination of measures to promote the use of EHR not only on the provider side but also among patients.

A number of tangible and timely recommendations emerge from the simulation experiments that evaluate policy options for promoting EHR adoption. For example, the results of this simulation suggest that financial incentives may affect the EHR adoption rate among hospitals and physicians but does not change the patients' use of EHR. We observe a similar effect when we increase training and education. Thus, policy makers need to balance their efforts in promoting EHR and focus on a broader approach rather than emphasizing single-policy options.

While sufficient data was not available to quantify the parameters in our model, we contend that the validity of the model can be assumed due to the following arguments: that the causal structure is supported by logic and previous research; the resulting dynamic behavior mirrors real-world observations; the parameters used in the model match real data points to some extent. The task remains, however, to establish reliable, valid and distinctive measures for parameter values and to empirically assess the simulation model. Given the growing importance of quality patient care in healthcare management, and given the small number of system

dynamics models that have addressed the dynamic nature of EHR adoption, we believe that the System Dynamics community can and must contribute to this research agenda.

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