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Nadiye O. Erdil
University of New Haven, NErdil@newhaven.edu

C. Robert Emerson
Binghamton University, State University of New York

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SIMULATION MODELING OF ELECTRONIC HEALTH RECORDS ADOPTION IN THE U.S. HEALTHCARE SYSTEM

NADIYE O. ERDIL
Ph.D.
Department of Systems Science and Industrial Engineering
State University of New York (SUNY) at Binghamton
PO Box 6000 Binghamton, NY 13902
607-768 2809
nadiye@binghamton.edu

C. ROBERT EMERSON
Professor
Department of Systems Science and Industrial Engineering
State University of New York (SUNY) at Binghamton
PO Box 6000 Binghamton, NY 13902
607-777 7663
remerson@binghamton.edu

ABSTRACT
Increasing the efficiency of the healthcare system in the United States is an important subject due to rapidly rising costs. Among many propositions to improve the operation of the system, adoption of Electronic Health Records is widely discussed. This study uses a system dynamics methodology to develop a simulation model of the adoption process that will allow for the exploration of policies. This paper presents the development and the preliminary findings of this model.

Keywords: *Electronic Health Records, System Dynamics, Simulation, Causal-loop Diagram*

INTRODUCTION
The United States has the largest and the most costly healthcare system in the world [1]. Quality and cost of healthcare services are affecting peoples' lives, the country's population health, and the economy. In searching for ways to improve delivery of healthcare services, better integration and effective utilization of Health Information Technology (HIT) with an emphasis on Electronic Health Records (EHRs) is one of the propositions that the healthcare industry has a near consensus on [2, 3,4,5]. However, EHR adoption in the United States healthcare system moves slowly [6,7, 8, 9, 10].

Healthcare systems are complex systems. The United States healthcare system, furthermore, is highly fragmented and has an intricate economic structure. Under these conditions, it is a challenge to understand how EHR adoption progresses in the system, and to evaluate what kind of interventions could speed up the process. The objectives of this study are to understand the factors influencing the adoption decision, how the dynamics of the system affects the adoption patterns and what kind of interventions can accelerate the adoption. To achieve these objectives, this research uses a System Dynamics (SD) approach. The SD methodology provides tools to uncover the dynamics of a system and to explore policy options through simulation. In [11], we developed a causal loop diagram of the EHR adoption process in the United States. In this paper, we continue with the development of a simulation model. First, we describe the general structure of the model, which consists of five sections. Then, we unfold the model by exploring each of these sections. Lastly, we present the preliminary findings of this simulation model.

METHODOLOGY

System Dynamics (SD) is a methodology that involves simulation modeling used in the analysis of complex systems. It focuses on the underlying reasons for changes over time. The cause and effect relationships and the feedback loops are the two fundamental concepts used to explain a change in a state of a variable. As opposed to discrete-event simulation models that constitute a large portion of simulation modeling, system dynamics simulation models are continuous simulation models. Continuous simulation modeling focuses on an aggregated view of a system, while discrete-event modeling involves detailed modeling of systems.

Introduced in the early 1960s by Jay W. Forrester to study urban dynamics problem, today SD has a wide range of application areas including healthcare. Applications of SD within the healthcare are also broad ranging from market analysis, feasibility assessment, chronic disease management, public health policy evaluations, planning ambulatory services, etc.

MODEL DEVELOPMENT

The main objective of this study is to develop an understanding of the EHR adoption process and to evaluate various policy options. A simulation model will provide grounds to attain this objective. The development process of this simulation model is the focus of this paper. This model is not intended to be a statistical forecasting tool, but rather to be a tool used for understanding of system behavior and the underlying dynamics. With this tool, policy options can be tested to assess the response of the system.

To build a stock-flow simulation model, first, the cause and effect relationships (feedback loops) among factors influencing the adoption process need to be revealed. The causal loop model explained in the following section captures these feedback loops.

CAUSAL LOOP MODEL (CLM)

Since the complete details of the CLM are in [11], only key points of the model are presented here. Factors included in the CLM, shown in Figure 1, have been identified through a literature review and the authors' prior studies in healthcare. Topics that are frequently discussed and issues that are stressed by the experts are the main sources. The system includes more factors than shown in the figure. However, to keep the model at a manageable level the number of factors is limited.

The focus of the model is the number of providers using EHR systems, represented by the factor *Adopted_Population.* Although stocks and flows are not commonly used in causal loop models, population factors are included in the model in that format to emphasize the focus. The flow *adopting* indicates the number of providers adopting per year.

The plus/minus signs on the arrows, in Figure 1, indicate how one factor changes because of a change in the other. The plus sign represents change in the same direction, while the minus sign corresponds to the opposite direction. The reinforcing and the balancing loops are shown with letters R and B, respectively.

FEEDBACK LOOPS

Feedback loops shown in Figure 1 capture the major issues in the EHR adoption process. Interactions of these loops determine the system behavior. Overall, the model focuses on the factors that influence the adoption decision of the non-adopted population in the provider sector. For example, increasing presence of EHR systems attracts the non-adopted population. This causal relationship is captured by the reinforcing Loop R1 in the figure, where the factor *fraction_of_population_adopted* is an input to the *attractiveness_for_potential_adopters*. The complete loop is shown in Figure 2.

EHR implementation cost is another factor that effects the non-adopted population in their decision to acquire EHR systems. Implementation costs increase as the market matures. While one would expect these costs to decline in a mature market, considering how fast the digital technology advances, and thus new and improved structures are needed to support the advancements, implementation costs increase as more enhanced products are released. With increased costs, attractiveness of EHR systems declines and fewer providers adopt. This feedback loop, shown in Figure 3, is Loop B1. The interested reader should refer to [11] for detailed discussions of all feedback loops shown in Figure 1.

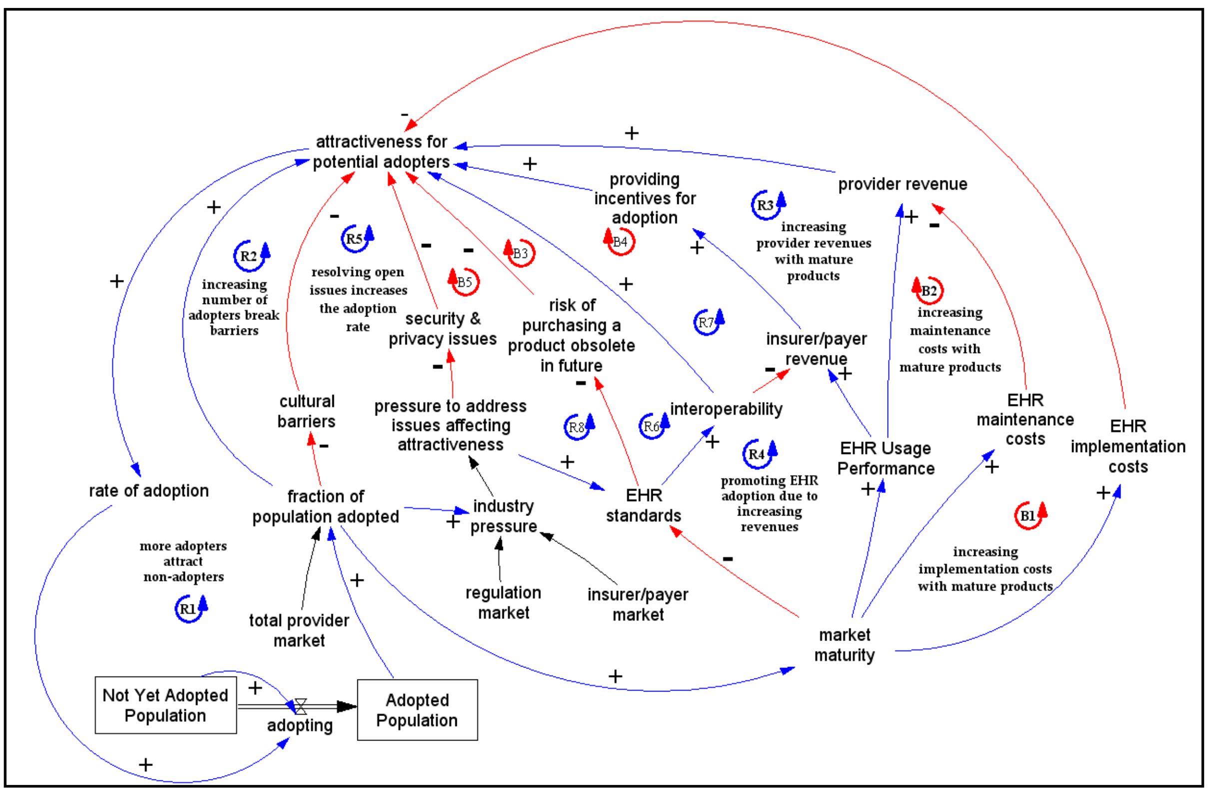


Figure 1 EHR adoption process in the U.S. Healthcare System - the Causal Loop Model

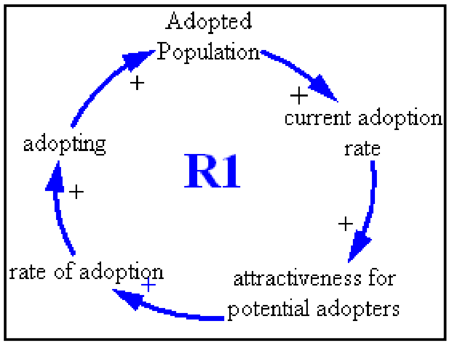


Figure 2 Loop R1 'more adopters attract non-adopters'

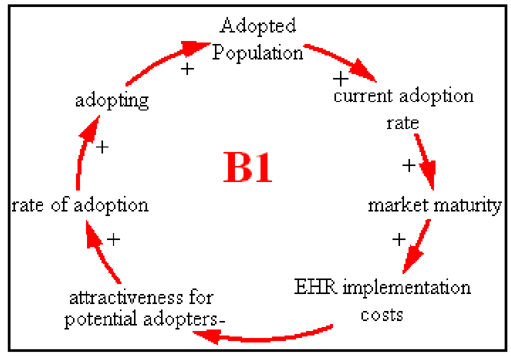


Figure 3 Loop B1 'increasing implementation costs with mature products'

SD MODEL

The simulation captures most of the feedback loops revealed in the causal loop study. Each feedback loop involves a number of interacting factors although only the top-level factors are displayed. By using a top-down approach, the feedback loops of the causal loop model steer the identification of factors included in the model. Some loops such as B5 and R8 "risk of purchasing a product obsolete in future" in the CLM shown in Figure 1 are currently eliminated due to the lack of data.

SD MODEL DESCRIPTION

In this section, first, assumptions of the model are reviewed. Later, the structure of the model is presented.

MODEL ASSUMPTIONS

The model is based on inpatient setting only which mainly consists of hospitals for two reasons. As opposed to outpatient setting, there is more data on hospitals' use of Health Information Technology; and studying one type of setting reduces model complexity, which is helpful in development of a starter model.

The model does not distinguish the classification of hospitals, which are the type, the location, the ownership, and the size. This study assumes that all hospitals are approximately the same size, and uses the American Hospital Association's statistics on the total number of hospitals and the total number of beds in the United States healthcare system to calculate the average.

The model does not represent providers in transition to EHR systems separately, but includes them in the non-adopter population.

EHR product and maintenance costs as well as costs of healthcare services are exogenous variables of the model.

The assumptions of the model at the factor level are the following: Once a provider starts using an EHR system, it does not abandon the system. Therefore, there is no outflow from the factor *Adopted_Population*.

The factor *EHR_maintenance_costs* represents the expenses associated with maintaining an EHR system. It includes several factors such as software updates, machine maintenance, user training, etc. These factors are not separately included in the model for simplicity; but are aggregated under *EHR_maintenance_costs*.

Although the total number of hospitals is a dynamic variable, a fixed number[1] is used in the model.

Under normal conditions, it is assumed that one percent of the population adopts EHR systems every year. This number is an average calculated from the adoption rates observed between the first time the term Computerized Patient Record was used in a publication - 1991, and 2005. During this period, over eleven percent of the population had acquired EHR systems.

MODEL STRUCTURE

The model's focus is the adopted population. The factor effecting the adopted population is the adoption rate multiplier, and thus, is the core of the model. Figure 4 shows the factors affecting the adoption rate. The model is designed to simulate the EHR adoption rate that is influenced by these factors.

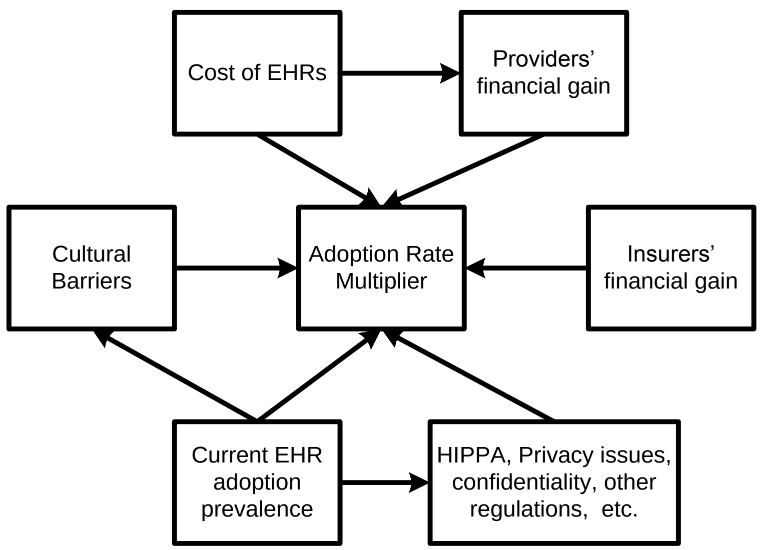


Figure 4 Factors affecting EHR adoption rate

By using the feedback loops identified in the CLM, the process of EHR adoption in the U.S. healthcare system is divided into five sections, as Figure 5 shows. To unfold the simulation model, these sections are used for guidance.

The main section includes the backbone of the model, the stock-flow structure that is the focus of the simulation. The whole population is divided into two categories: providers with and without EHRs, *Adopted_Population* and *Not_Yet_Adopted_Population* respectively. The model assumes that a certain percentage of non-adopters move into the adopters' pool each year. The attractiveness of EHR systems to the non-adopters, which is represented by the factor *adoption_rate_multiplier*, influences this number. Multiple factors influence the attractiveness.

The provider section contains one of the factors that influence the attractiveness of EHR systems, *provider_multiplier*. This part of the model computes an average annual return on

[1] The total number of hospitals in 2005.

investment (ROI) for an average size hospital, given that an EHR system is in use. High annual ROI in provider facilities with EHRs attracts the non-adopter population to EHR systems.

Similar to the provider section, the insurer\payer section calculates a multiplier that represents the insurers and payers approach to the electronic health record systems. The model computes the financial impacts of EHR systems to the insurer\payers. If a positive impact is observed, then the insurer\payer supports the acquisition of such systems at provider locations and establishes transaction systems with the providers that would encourage this acquisition, and vice versa.

The cost section integrates EHR implementation and maintenance costs into non-adopters' decision-making on whether to acquire EHR systems. It calculates an average implementation and maintenance costs based on the number of beds in a facility.

The environment section includes non-financial factors that effect the non-adopted population, such as cultural barriers, security and privacy issues, etc.

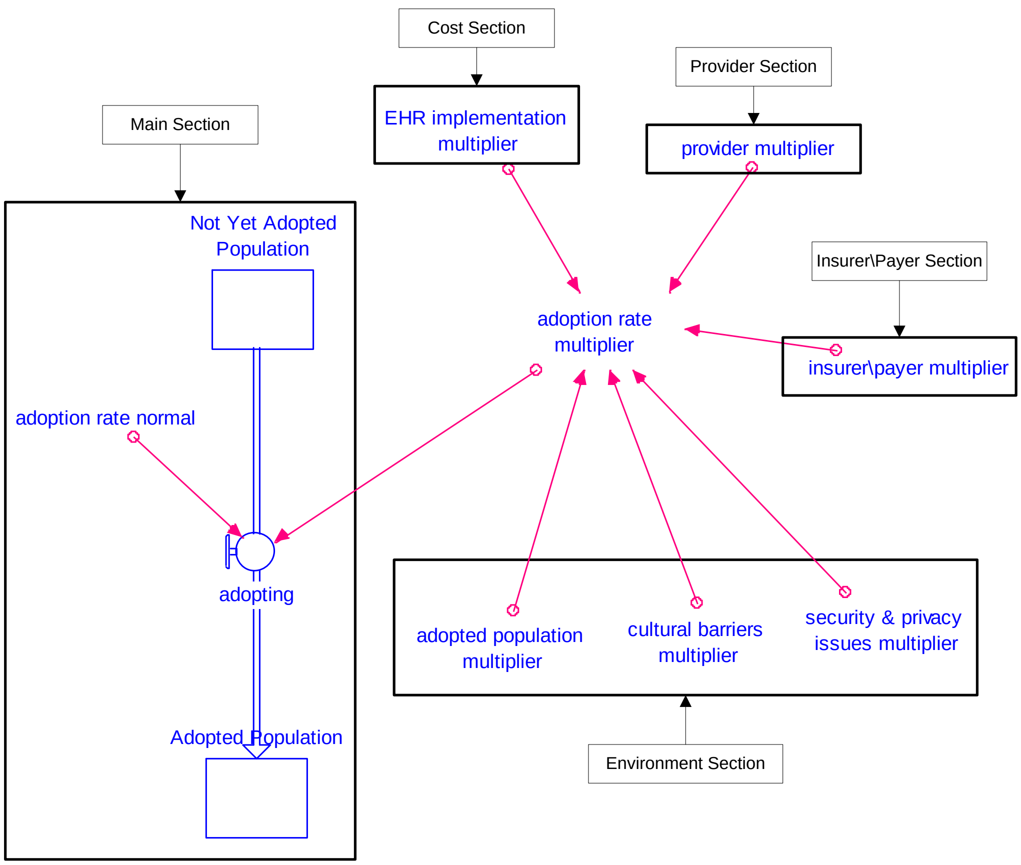


Figure 5 Main factors in the EHR adoption process in the U.S. Healthcare System – Sections

MODEL VALIDATION AND ANALYSIS

This section begins with the explanation of the model validation process. Then, the results of the base run simulation and the sensitivity analysis are discussed.

VALIDATION

Of the three test types – structure, behavior, and policy, - the structure tests have been extensively applied to the simulation model developed for this study. These tests are listed below. Behavior and policy implications tests, that judge whether a model generates plausible behavior, were not formally explored. The system that was modeled is fairly young, and thus it was difficult to interpret the patterns of behavior in terms of their plausibility. Among behavior tests, only the behavior-sensitivity test was performed. The details of this test are given in the Sensitivity Analysis section.

Structure verification test: The structure verification test assesses whether the model structure is consistent with the knowledge about the real system being modeled. The organization of model variables of this study was verified by walkthroughs of each section explained in the Model Structure section and comparisons with the causal loop diagram in Figure 1. Mental model verification included reviews of the model by professionals in the healthcare field.

Parameter verification test: The parameter verification test checks whether all parameters in the model have real world correspondence and that their values are consistent with the numerical knowledge of the system. All factors of the model in this study have been extracted from the literature about the real system and the author's prior studies in healthcare. Values of all parameters were derived from studies in the literature about the real system.

Extreme condition test: The extreme condition test examines whether the model exhibits a realistic behavior when subjected to extreme values. In this study, cost was identified as one of the significant factors effecting the adoption decision; therefore, extreme condition tests were performed with factors that were cost related. The response of the model to these tests was neither unexpected nor unrealistic.

Dimensional consistency test: The dimensional consistency test checks whether all equations and the dimension of all the variables in the model are specified and balanced. The "Check Units" feature in Stella that performs a unit consistency check on all model variables was used to verify the dimensional consistency in the model.

Boundary adequacy test: The boundary adequacy test assesses whether all relevant structure of the system being modeled is included in the model and the important concepts used to address the problem are endogenous to the model. In this study, the benefits of EHR systems and barriers of the adoption process formed the general structure of the model; and consistent with the purpose of the model, all major factors were generated endogenously.

ANALYSIS – BASE RUN

The simulation starts from 2005. The base run is executed under the assumptions explained in the Model Assumptions section. It is important to understand that much can be gained by further studies and variation of the assumptions used. With the current set of data, EHR adoption patterns from the model output are shown in Figure 6. An S-shape growth is observed on the number of EHR users indicated by the blue line marked with a 1 on the graph. According to this output, in about fifty-five years, ninety percent of the provider population would be using EHR systems. The number adopting follows a slow growth in the beginning, accelerates in the middle, starts to slow down as saturation begins, and finally stops at maturity. This S-shape growth behavior is common in new product markets.

Figure 7 shows the EHR usage performance pattern and the expected financial gains and losses to the provider attributed to EHR system usage. The factor *EHR_usage_performance* represents the maturity level of EHR systems in a given time period. Indicated by the purple line marked with a 3 on the graph, EHR products mature over time. Since EHR usage performance effects the operation of the system functions, its impact on these functions increases as the usage performance improves. Thus, patterns of expected financial gain and loss follow the EHR usage performance pattern. The graph indicates that once the EHR products enter a mature state (middle section of the S-curve), the net financial gain considerably increases, creating an attractiveness to potential adopters.

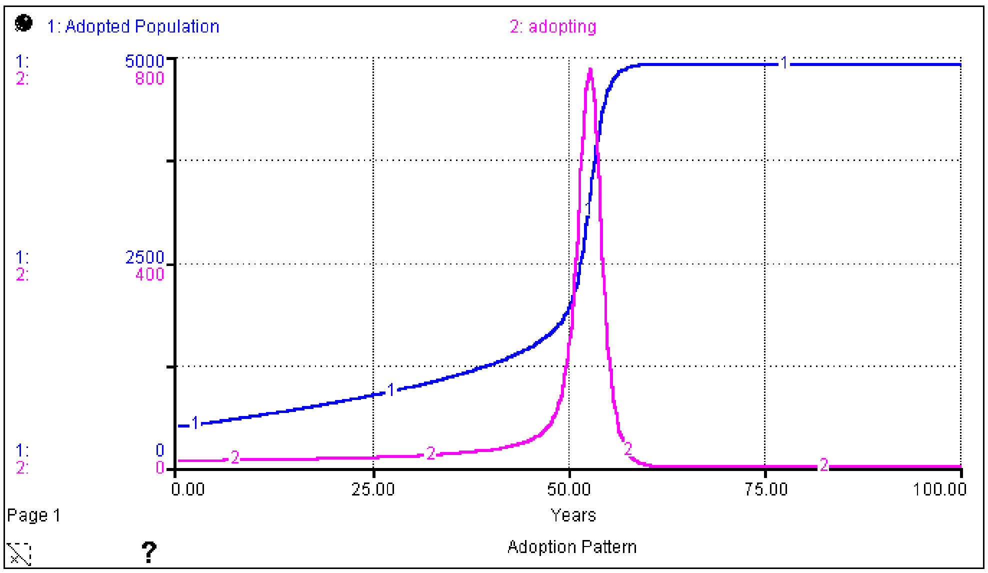


Figure 6 EHR adoption pattern - Base Run

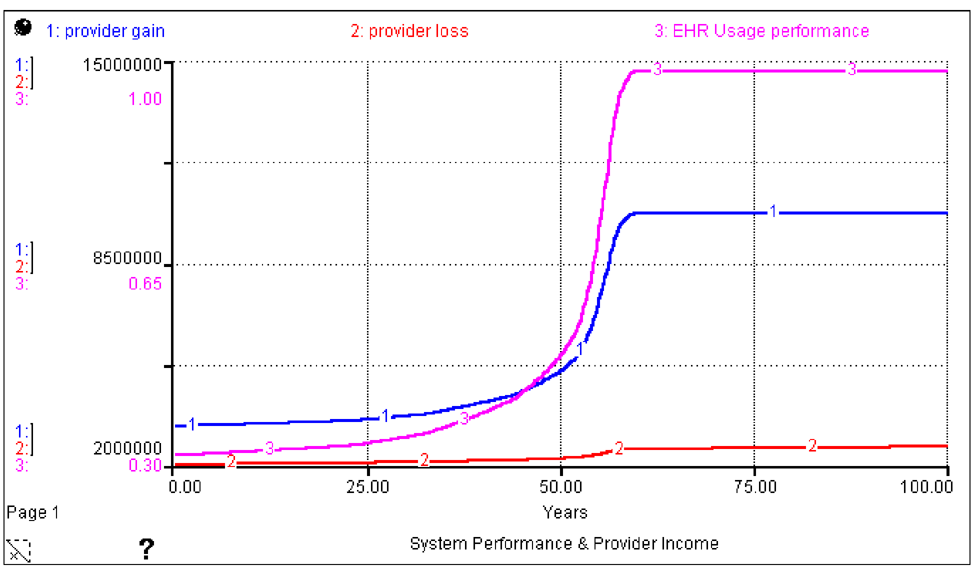
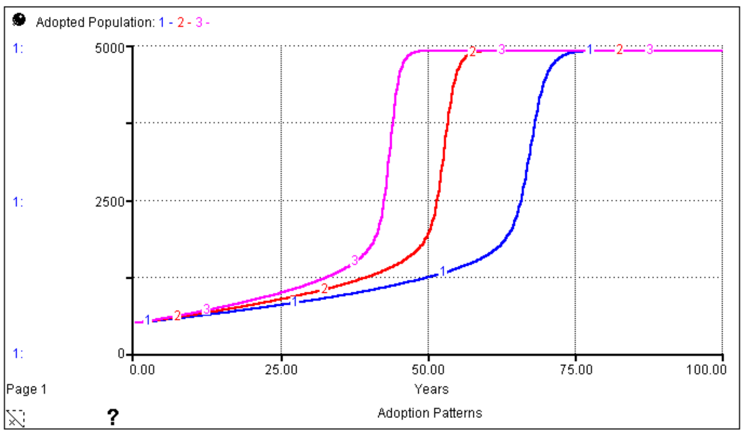


Figure 7 Provider Income Patterns – Base Run

SENSITIVITY ANALYSIS

The parameter sensitivity test assesses how robust the model is to uncertain decisions or assumptions about the data. For the SD model, nine factors were varied one at a time by ±20 percent to analyze the effects on the outcome of the model. The nine factors chosen for sensitivity analysis were related to the adoption rate, system costs, length of stay, utilization of services, medical mistakes, and the organization size.

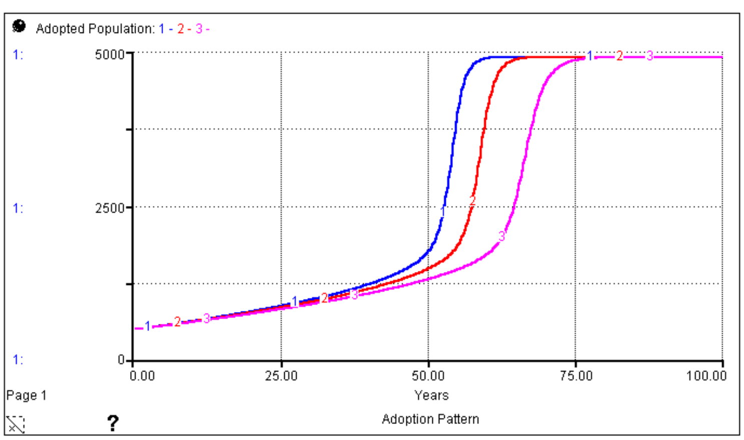
Adoption Rate: The model assumes that under normal conditions, one percent of the non-adopted population acquires EHR systems. This is represented by the factor *adoption_rate_normal*. With higher values of this factor, a shorter time span to full adoption was expected. Figure 8 shows the results of varying this factor. As expected, run #3 – with the highest adoption rate normal, gave the shortest time. Judging by the gap between each output, it was concluded that the model was sensitive to this factor.



Run #	Input Variables adoption_rate_normal
1	0.008
2	0.010
3	0.012

Figure 8 Sensitivity Analysis - *adoption_rate_normal*

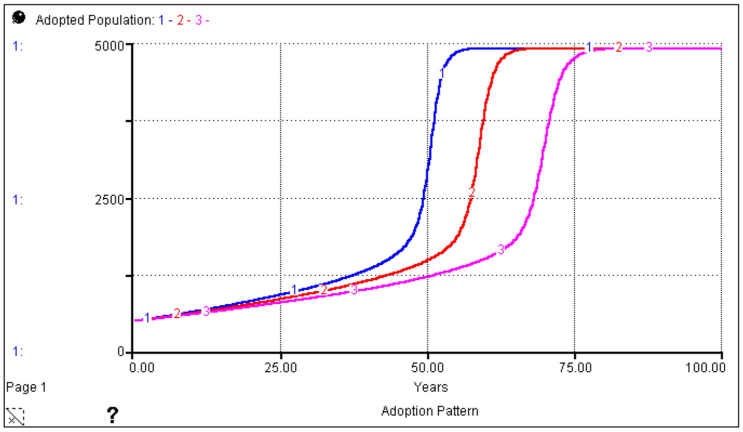
System Costs-Implementation Cost per Bed: Cost of EHR systems is one of the major barriers to adoption; therefore, it was expected that the model was sensitive to cost related factors. Figure 9 shows the response of the model to changing values of the factor *implementation_cost_per_bed*. The model output indicated that as the per bed cost increases the time to full adoption lengthens.



Run #	Input Variables implementation_cost_per_bed
1	4400
2	5500
3	6600

Figure 9 Sensitivity Analysis - *implementation_cost_per_bed*

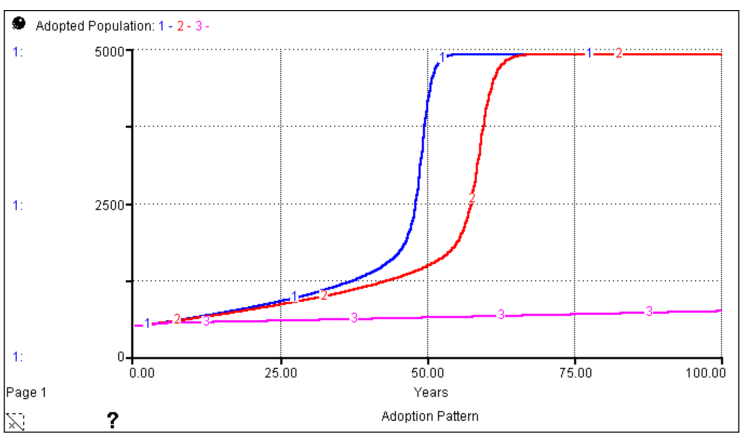
System Costs- Maintenance Cost Per Bed: Results similar to the implementation costs per bed were expected with the sensitivity analysis on the maintenance costs. The model output, shown in Figure 10, exhibited the same patterns as in the previous case.



Run #	Input Variables maintenance_cost_per_bed
1	9086
2	11358
3	13629

Figure 10 Sensitivity Analysis - *maintenance_cost_per_bed*

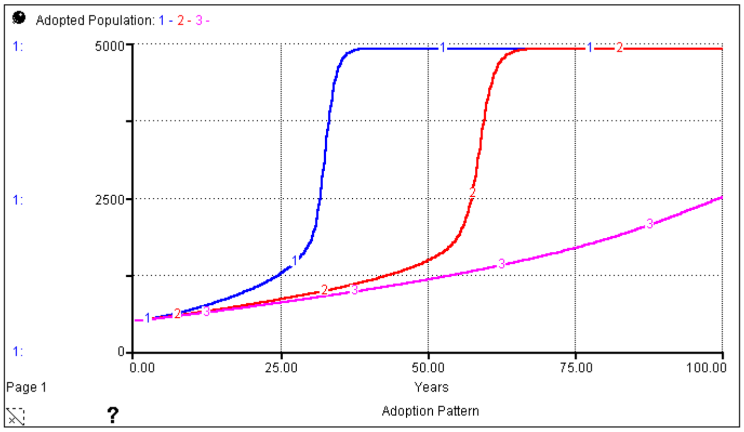
System Costs-Annual Price Increase on EHR products: The factor *EHR_implementation_normal* reflects the annual price increase on EHR products. Similar to the factor per bed costs, the model was expected to be sensitive to this factor since it was a cost related parameter. The model output, shown in Figure 11, asserted this argument. Moreover, the results indicate that this cost factor is one of the most sensitive factors in the model. The run #3, representing +20 percent change in annual price increase, shows almost no new adoptions in the system.



Run #	Input Variables EHR_implementation_normal
1	0.808
2	1.010
3	1.212

Figure 11 Sensitivity Analysis – *EHR_implementation_normal*

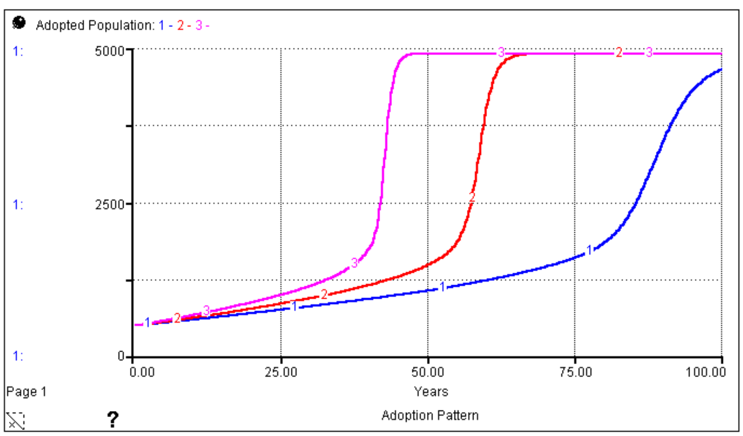
System Costs-Annual Price Increase on maintenance: The factor *EHR_maintenance_normal* reflects the annual price increase on the maintenance of EHR products. Shown in Figure 12, the output of the model indicates that this is another sensitive factor. Comparing Figure 11 to Figure 12, increase in implementation costs vs, maintenance costs, it was interesting to see that while higher implementation costs results in longer time to full adoption, lower maintenance costs accelerates the adoption. This indicates that the higher initial (short term) and the lower long term expenses are more influential in adopting decision than the lower initial and the higher long term expenses.



	Input Variables
Run #	EHR_maintenance_normal
1	0.8008
2	1.0010
3	1.2012

Figure 12 Sensitivity Analysis – *EHR_maintenance_normal*

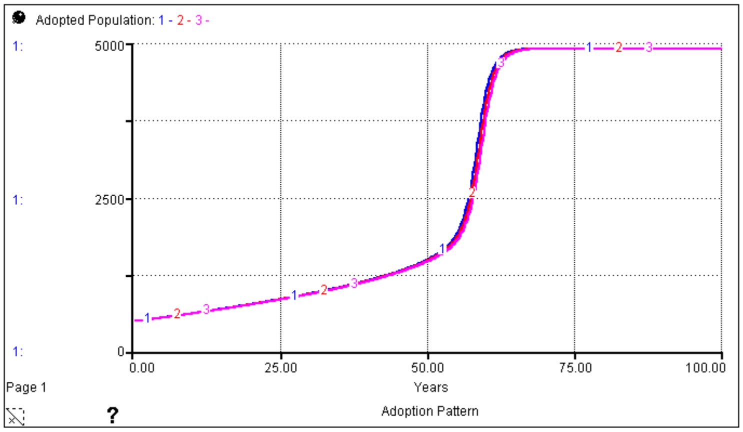
Length of Stay: The factor *LOSMPB* represents per bed cost of length of stay. Since this factor positively effects both the provider and the insurer\payer multiplier, a change in its value was expected to impact the model output. The time gaps between the base run and the alternatives confirmed that the model was sensitive to this factor.



	Input Variables
Run #	LOSMPB
1	386284
2	482855
3	579426

Figure 13 Sensitivity Analysis – *LOSMPB*

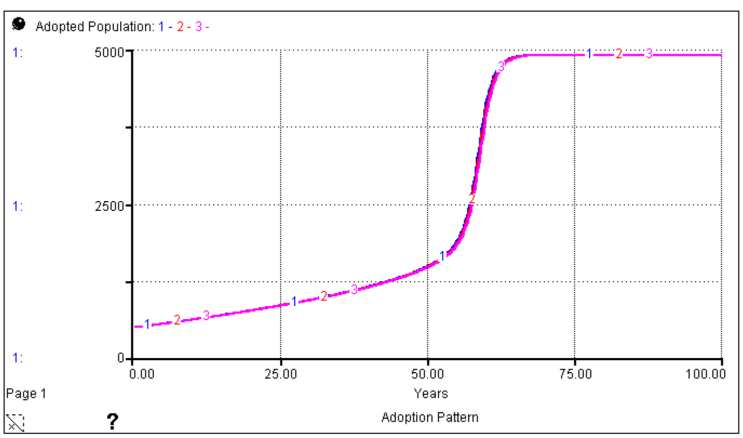
Utilization of Services: The factor *uos_mult* denotes a utilization of services multiplier that represents the fraction of service utilization costs lost to the provider. It is a cost related factor; however, compared to the other cost related factors its impact on the provider multiplier is not considerable. Therefore, the model was not expected to respond significantly to the changing values of this factor. As anticipated, the model output, shown in Figure 14, did not show a noticeable change of pattern.



Run #	Input Variables uos_mult
1	0.16
2	0.20
3	0.24

Figure 14 Sensitivity Analysis – *uos_mult*

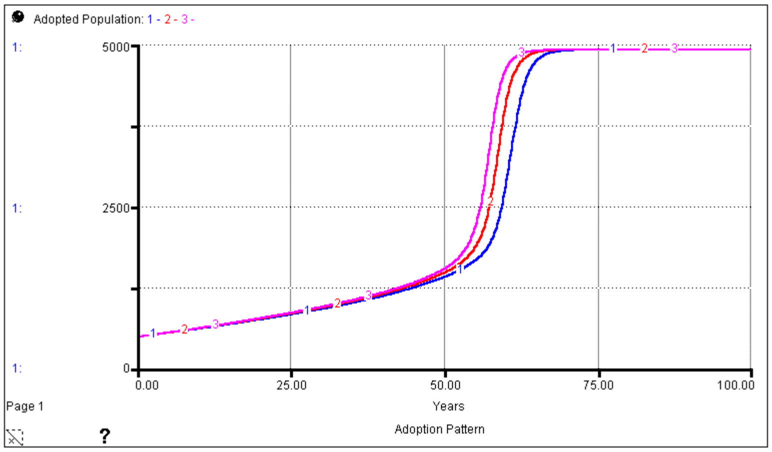
Cost of Medical Mistakes per Bed: Cost of medical mistakes per bed is represented by the factor *MMMPB* in the model. This factor is an input to the provider loss computations. An increase in the value of this factor increases the financial loss for the provider. Therefore, a delay in reaching a full EHR adoption was expected with higher values of this factor. However, results shown in Figure 15 indicated otherwise. This was attributed to the reason that the factor was also an input in the insurer\payer gain computations. The more financial gain there was for the insurer, the greater the incentive programs were for the providers to use EHR systems. Therefore, for providers on one hand there is the financial incentives generated by the insurer\payers encouraging the use of EHR systems, and on the other, there is the financial loss caused by the use of the system. The output of this sensitivity analysis showed that the effect of the factor MMMPB from the insurer section balanced the effects from the provider section. Therefore, the model did not show sensitivity to the factor *MMMPB*.



Run #	Input Variables MMMPB
1	3490
2	4362
3	5234

Figure 15 Sensitivity Analysis – *MMMPB*

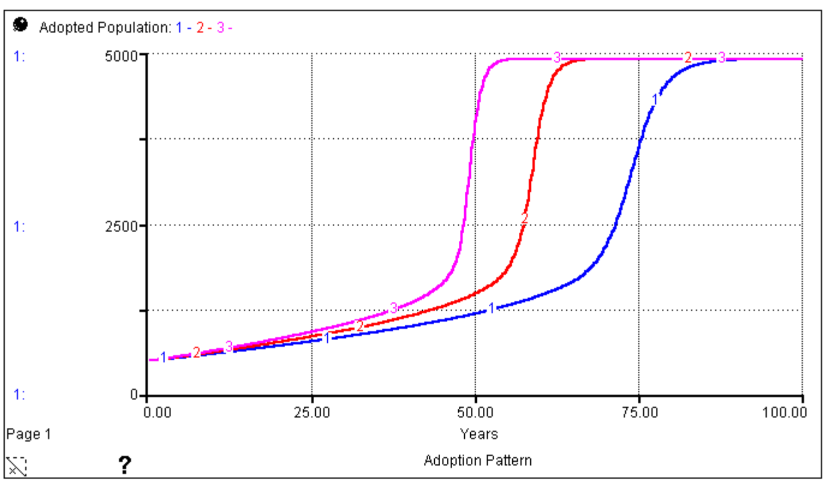
Billing-Coding-Charging Errors: The factor *BCCEMPB* represents per bed cost of billing, coding, and charging. Similar to other cost related factors, the model was expected to respond to changes in this factor. However, the response of the model, shown in Figure 16, indicated otherwise. The reason is similar to the case explained in the previous test. This is a factor affecting both the provider and insurer\payer, in the opposite direction. Thus, a change in one balances the change in the other; and the net change is not significant enough to alter the model behavior.



	Input Variables
Run #	BCCEMPB
1	246913
2	308642
3	370370

Figure 16 Sensitivity Analysis – *BBCEMPB*

Total Number of Beds: Total number of beds in the system is represented by the factor *TNB.* This factor is an input to all financial calculations. Thus, the model was expected to be sensitive to this factor. Since, cost becomes a major impediment as the size of the organization gets smaller [**1**, **2**], a slower adoption pattern was expected with smaller values of *TNB*. Moving from the line marked with a 1 to the line marked with a 3 in Figure 17, deceleration in the adoption patterns were encountered with decreasing number of beds.



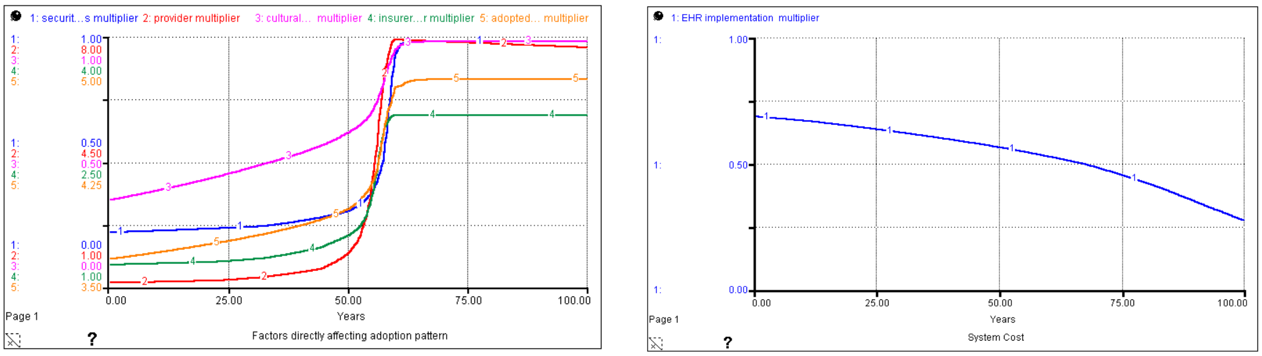
	Input Variables
Run #	TNB
1	641849
2	802311
3	962773

Figure 17 Sensitivity Analysis – *TNB*

MODEL IMPLICATIONS

The EHR adoption process in the United States healthcare system follows a common trend seen in new technology-product markets. An s-shape pattern is projected by the model. Until approximate forty percent adoption rate is reached, a slow growth is displayed. Then acceleration in adoption is observed which leads to almost a full adoption in ten years. After ninety-six percent adoption rate is attained, the growth slows down again. The number adopting reaches its peak around when the adoption rate is seventy percent.

Factors directly affecting the EHR adoption, shown in Figure 18, also exhibit similar behaviors. Despite that fact that the input functions for these factors are not all s-shape; all factors, except system cost, show an s-shape output pattern following the trend in the current adoption rate. System cost, displayed in Figure 18b, presents a different pattern, because it is not dependent on the current adoption rate. It is based on the assumption that costs increase annually by one percent [18]. The decreasing trend, which indicates that the negative influences on the adoption patterns get worse, is due to the consistent increase in the systems cost.



(a) (b)

Figure 18 Factors directly affecting adoption pattern – BASE RUN

The factor *provider_multiplier* that represents the willingness of the non-adopter population to adopt EHR systems is indirectly dependent on the EHR system performance, which in turn, is dependent on the maturity level of the market. Shown in Figure 19, *market_maturity* and *EHR_usage_performance* exhibit almost identical behaviors, while the *provider_multiplier* behavior is slightly different. The reason is that there are other factors influencing *provider_multiplier*. Sophisticated EHR products, a result of a mature market, improve performance metrics. However, enhanced products require enhanced support structure, which increases the cost of acquiring and maintaining the systems. Since cost is a factor also effecting *provider_multiplier*, a slight change in behavior is observed.

Based on the analysis presented in the Sensitivity Analysis Section, the model is sensitive to cost related parameters, both implementation and maintenance. Among the factors that are affecting both providers and insurer\payers financial gains, the model is not responsive to factors that generate effects in the opposite direction.

MODEL LIMITATION AND FUTURE WORK

In our earlier work [11], we presented a causal loop model (CLM) of the EHR adoption process in the United States healthcare system. In this paper, we discuss a simulation model developed from this CLM. This model as it stands focuses on the providers' side of the adoption process, and includes the insurer\payers partially. Including other stakeholders such as vendors, patients, etc. would improve the model. Second, these stakeholders' input should be taken in the model development and verification phases. Without these, the model is limited and theoretical. In addition, the model needs rigorous data to strengthen its implications even though it is not designed to serve as a statistical based inference tool.

There are some simplifying assumptions of the model that are not consistent with the real world situation. For example, in the model, there is no going back to the non-adopted population once entered in the adopted population. Considering the financial costs of acquiring EHR systems, it is unexpected to see a move from the adopted population to the non-adopter population. However, it still is possible. These assumptions, given that data becomes available, could be altered.

With a complete simulation model, future work lies in the exploration of policy options. This analysis will help us understand what type of interventions can accelerate the EHR adoption process, how these interventions can be integrated in the current system, and given that a policy(s) is executed what the outlook will be.

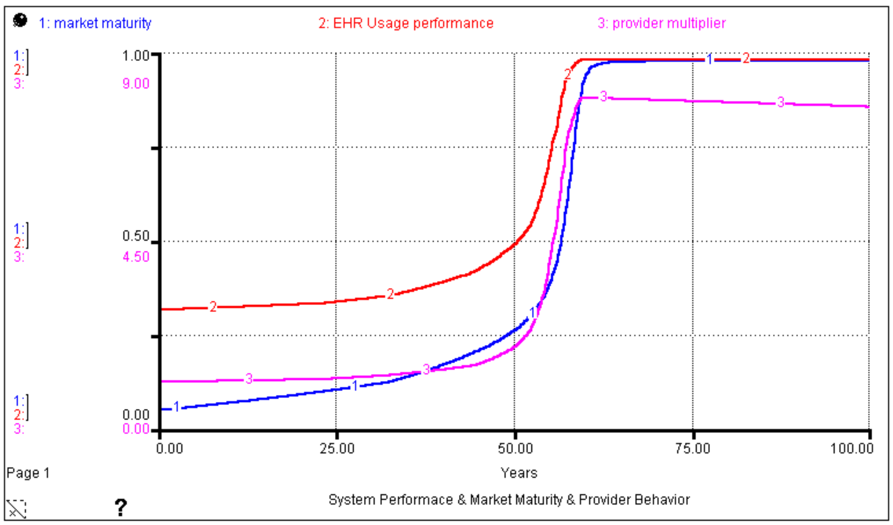


Figure 19 Market - Performance Metrics - Non-adopter Behavior - BASE RUN

CONCLUSION

This study focuses on the EHR adoption process in the United States healthcare system. The goal is an understanding of the factors influencing the adoption process, how the dynamics of the system effects the adoption patterns, and what kind of interventions can accelerate the adoption. To address this problem, a System Dynamics (SD) methodology is followed. This approach has provided grounds to bring systems perspective on the topic, something that has yet to be exploited in the literature. First, a causal loop model of the system is developed. Then, an SD simulation model is developed. This simulation model is the focus of this paper. The model represents the general structure of the system from the providers' perspective. Nonetheless, it offers a theoretical foundation to gain insights about the dynamics of the system. Future work is to evaluate various policy and regulatory decisions by using the model.

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About the Authors

Nadiye O. Erdil, (B.S., Computer Science – M.S., Industrial Engineering) received her Ph.D. in Industrial and Systems Engineering from Binghamton University in Spring 2009. Her research interests include health systems and health information systems.

C. Robert Emerson is professor of Industrial and Systems Engineering at Binghamton University. His research interests include finding solutions to policy questions within complex systems. The applications range from manufacturing to healthcare.