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Modeling the Adoption of Identification Standards Within the Healthcare Supply Chain

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MODELING THE ADOPTION OF IDENTIFICATION STANDARDS WITHIN THE HEALTHCARE SUPPLY CHAIN

MODELING THE ADOPTION OF IDENTIFICATION STANDARDS WITHIN THE HEALTHCARE SUPPLY CHAIN

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ABSTRACT

The adoption of identification standards and its associated technology in the healthcare supply chain has been slow over the past twenty five years, despite the evidence of the benefits that can be achieved. The widespread use of identification standards in the form of barcode labeled medical products can contribute to the reduction of point of care errors and can increase the efficiency of healthcare supply chain related processes. This research is focused on the analysis of the adoption of identification standards in the healthcare supply chain with a particular focus on the healthcare provider adoption challenges. The research is divided into two phases.

The first phase develops an extensive literature review on technology adoption with a particular focus on data standards. This adoption process is compared with the adoption of Electronic Health Records (EHR) and Electronic Data Interchange (EDI); main conclusions from the identification standards literature are presented, and a conceptual model to explain the identification-standards adoption process is proposed.

The second phase proposes a model for identification standards adoption using a system dynamics modeling approach. The model builds on previous findings associated to the factors affecting identification standards adoption and relates the specific elements to the adoption rate via a causal loop diagram (CLD). The model is formulated in two stages. In the first stage, the Bass Diffusion Model (BDM) of technology adoption is adapted to simulate the adoption of identification standards supporting technologies. The second stage uses most of the factors defined in the CLD to develop a simulation model. A sensitivity analysis identifies relevant model parameters that facilitated the design of interventions to move the adoption process

forward. Finally, the effects of some possible interventions are simulated using the validated model. The model provides an illustration of the use of system dynamics models and diffusion theory to understand an important policy problem reported in the literature and not yet solved. Also this research informs real world practitioners and the academic community on issues like the lack of data and other challenging aspects of empirical research that can be addressed with the proposed model and methodology.

This dissertation is approved for recommendation
to the Graduate Council.

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DEDICATION

This dissertation is dedicated to my beloved husband Ignacio and my two little ones Juan Pablo and Ana Sofia. It took a lot of effort on my side but also a lot of patience and support from their side. We grew together in the process, and I am sure we will keep wonderful memories about this journey forever.

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1. Introduction

1.1 Motivation and Brief Research Topic Description

Data standards also referred to as identification standards, have been around since 1974 when the Universal Product Code (UPC) was developed within the grocery industry. Since then other industries have tried to adopt similar standards in order to realize the benefits achieved by the grocery industry with the UPC adoption, which according to (Garg, Jones, & Sheedy, 1999) have been estimated to be approximately 17 billion dollars.

Currently the healthcare supply chain lacks identification standards for the products that flow through the supply chain and for the locations associated with this product flow. Several benefits regarding identification standards adoption associated with supply chain process efficiency and patient safety improvements have been identified in many studies. The broad benefits of adopting identification standards include efficient traceability (Rosenfeld & Stelzer, 2006), improved ordering, invoicing and receiving processes (CSC, 1996), reduced data cleansing efforts (Accenture, 2006), ability to better monitor product recalls, track expiration dates and product authentication (Hefflin, 2005) among others.

Despite the estimated benefits of identification standards adoption the healthcare industry is moving at a slow pace. As reported by (Simpson & Kleinberg, 2009) the main contributors for the slow adoption include market drivers and technology issues. There is a major "chicken versus egg" problem on unit of use bar coding (i.e printing a barcode label at the smallest unit of use on every pharmaceutical and medical supply). Initially manufacturers were unwilling to barcode their products since they knew hospitals did not have the scanners to read them and

hospitals were reluctant to invest in barcode scanning technology if the products did not come labeled with barcodes. In the technology side, major healthcare information systems vendors have lagged behind in providing robust barcode enabled applications to support supply chain processes.

This research project investigated the identification standards adoption process within the healthcare supply chain and developed a theoretical model based technology diffusion theory; a system dynamics modeling approach was used to model this process. The model allowed for the identification of the factors affecting the identification standards adoption process, also facilitated the understanding of the system (healthcare supply chain) behavior and allowed for the design and test of policies to move the system forward.

In Section 1.2 background information on relevant elements related to this research topic are provided. The research problem is defined in Section 1.3 along with the research questions. The document overview is presented on Section 1.4.

1.2 Background

1.2.1 Healthcare supply chain

The healthcare supply chain includes a variety of members, including manufacturers, distributors, transportation companies, hospital receiving and materials management departments, nursing units, hospital floors and finally the patient. Figure 1 below illustrates the basic product flow within the healthcare supply chain.

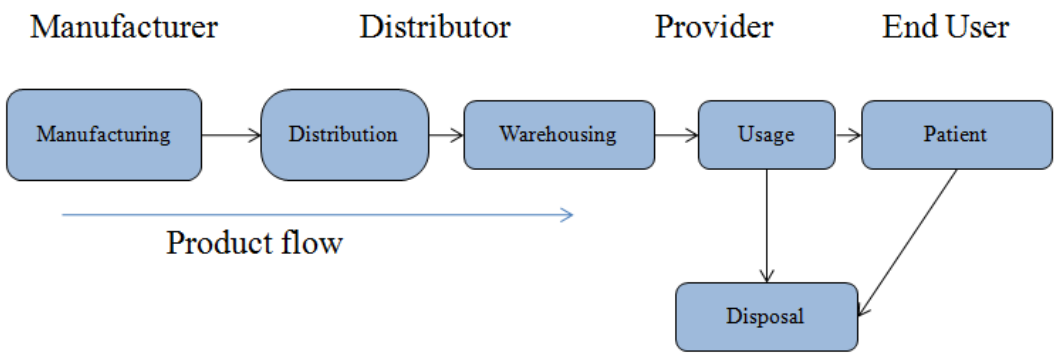

Figure 1. Healthcare Supply Chain (adapted from CSC, 1996)

Each healthcare supply chain member performs specific processes with the ultimate goal of assuring product availability for clinical use (i.e consumption at the point of use). These processes can be classified as: external to the healthcare provider, such as, manufacturing and distribution; and internal, such as, ordering, receiving, storage, picking and floor replenishment. According to (ERG, 2006) the healthcare supply chain members can be grouped in the following categories:

- Transacting members
    - Manufacturers
    - Distributors
    - Group Purchasing Organizations (GPO)
    - Healthcare providers (hospitals)
- Payers
    - Centers for Medicare and Medicaid Services
    - Insurance companies
- Industry Groups

    - Association for Healthcare Resource and Materials Management (AHRMM)
    - GS1 Healthcare User Group (HUG)
    - Healthcare Information and Management Systems Society (HIMSS)
    - Department of Defense (DoD)
    - Strategic Marketplace Initiative (SMI)
- Food and Drug Administration (FDA)
- Technology providers

Transacting members differentiate from other members because they are directly involved in the transactions required to move the product from the manufacturing plant to the point of use at the hospital location.

The healthcare supply chain can be compared to other supply chains. There are a number of important distinctions as presented by (Simpson & Kleinberg, 2009), (CTL, 2006) between the healthcare supply chain and other supply chains like the Consumer Packaged Goods (CPG) that represent a challenge for identification standards adoption, those include:

- The fragmentation of the healthcare supply chain. There are no dominant players to drive favorable changes in industry practices, to force investment in new technology and to promote process change.
- The segregation of product, information and money flow. The actual user or consumer of the products is not the payer in most cases; also the decision maker (e.g. doctor or a nurse) is neither the consumer of the product nor the payer (insurance or government). This makes product, information and money flow along disjointed paths as opposed to paralleling each other.

1.2.2 Identification Standards

Identification standards as defined by (Hubner & Elmhorst, 2008) are a building block for the efficient product flow and its associated transactions for a given supply chain. The issue of lack of data standards has been reported in a recent survey (Nachtmann & Pohl, The State of Healthcare Logistics: Cost and Quality, 2009) as a major challenge to achieve supply chain excellence in the healthcare sector. Two types of identification standards will be addressed within this research: product identification standards and location identification standards.

Product Identification Standards

For healthcare supply chain management purposes, having a unique identifier at the smallest unit of use would streamline pharmaceutical and medical supply chain processes and payment systems. This could also make point of care scanning possible (Simpson & Kleinberg, 2009). The point of care scanning concept is similar to the retail store Point of Sale (POS) checkout process where every product leaving the store must be checked out for billing purposes. The same concept should be transferable to the hospital setting.

Different identification standards exist within the healthcare supply chain which means no standard is really in place. Pharmaceutical products have used the National Drug Code (NDC) since 1974 due to specific Food and Drug Administration (FDA) regulations. The most recent regulation requiring manufacturers labeling pharmaceutical products at the smallest unit of use have forced most pharmaceutical manufacturers to print NDC numbers in linear barcode (one dimensional) format. For medical devices and general medical surgical supplies the use of the Universal Product Number (UPN) since 1995 has been the norm because of the efforts of the

Department of Defense on various internal pilot projects. About 75% of medical products carry a UPN (Hefflin, 2005).

GS1 standards (formerly EAN UCC) and Health Industry Business Communication Council (HIBCC) standards are also identification standards used by some healthcare supply chain members. A survey referenced by (Bix, Clarke, Lockhart, Twede, & Spink, 2007) reports 59% of the respondents using GS1 standards and 39% using HIBCC standards. One major difference between GS1 standards and HIBCC standards is that the former is a global standard used in many other industries and HIBCC standards were developed specifically for the healthcare industry. As of today the issue of having a unique identifier at the smallest unit of measure, unit-dose for pharmaceuticals and unit-of-use for medical products, has not been solved.

Location Identification Standards

Location identification standards are referred to as the unambiguous identification of every supply chain transacting member in order to facilitate ordering, contract pricing and rebate processing. Currently supply chain members are identified by customer account numbers issued by each transacting member (e.g. each health care provider can assign a different number to describe the same manufacturer). Under these conditions is not possible to uniquely identify any supply chain transacting member. The lack of unique location identifiers generates supply chain process inefficiencies which can be reduced by the proper use of the standards.

Technology

Technology plays an important role in identification standards adoption and implementation (Langabeer, 2005). The level of current process automation at the healthcare provider level or

any other transacting member in the healthcare supply chain will have an impact on how identification standards can be adopted.

Technology allows for capturing the product related information as it moves through the supply chain and also helps to store and process product related information as well as the transactions associated with it. Figure 2 illustrates the relationship between identification standards and technology.

The technology associated with identification standards, which should be implemented by any given transacting member within the healthcare supply chain in order to adopt identification standards, can be classified in two groups:

- Auto Identification and Data Capture technologies (Auto ID DC). Auto ID DC technologies such as barcode or Radio Frequency Identification (RFID) technology, can increase process efficiency, reduce data entry errors and free staff to perform more value added functions.
- Information systems (supply chain, materials management or purchasing systems). Information systems such as Materials Management Information System (MMIS) are applications used to support internal and external supply chain processes within a given supply chain member.

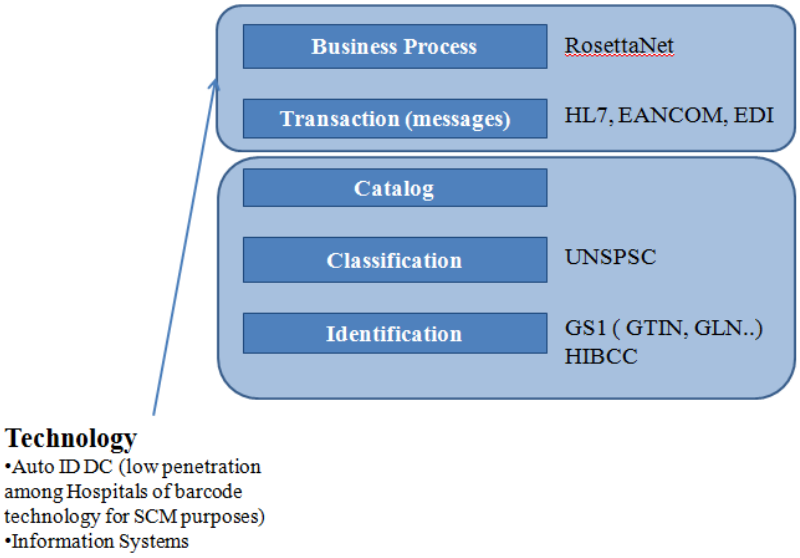

Figure 2. Supply Chain Standards (adapted from Hubner and Elmhorst, 2008)

As an example, at the healthcare provider level, the technological capabilities related to barcode enabled processes for internal supply chain management transactions and the information systems supporting those specific transactions will have an impact on the identification standards adoption process. According to a 2007 American Hospital Association (AHA) survey (AHA, 2007), less than 16% of hospitals are fully using barcode technology for supply chain management purposes; the use of RFID is less than 3%. Technology has been referenced as one of the major barriers to identification standards adoption (Nachtmann & Pohl, The State of Healthcare Logistics: Cost and Quality, 2009).

This research is focused on the adoption of identification standards along with the required technology to automate the transactions and business processes that make possible the efficient flow of product from the manufacturer to the point of use at the healthcare provider level.

1.2.3 Several attempts and initiatives

The adoption of identification standards and barcode technology began within the grocery industry around the mid seventies. The sequence of relevant events documented by (HIMSS, 2003) illustrates how the healthcare industry has tried to adopt identification standards but have not been successful, those events include among others:

- In 1983 the Health Industry Business Communications Council (HIBCC) was established to promote the adoption of identification standards. The standards developed by HIBCC where specific for the healthcare industry and where adopted mainly by manufacturers.
- In 1989 the use of barcode technology for point of care applications was promoted among hospitals.
- In 1995 the Efficient Consumer Response (ECR) in grocery industry was defined as the reference point to determine how ECR practices could apply to healthcare supply chain, since major industry parallels between grocery and healthcare industry were identified. The result from this effort is the Efficient Healthcare Consumer Response (EHCR) (CSC, 1996) study, which identified more than six billion in potential savings for barcode technology adoption within the hospital supply chain.
- In 2000 the Institute of Medicine presented a report (Kohn, Corrigan, & Donaldson, 2000) which estimated that up to 98,000 lives are lost a year due to preventable medical errors. Many of these errors could likely be avoided by the use of technology such as barcode technology, in particular for the purpose of Bedside Point of Care (BPOC) scanning.

- The 2004 FDA rule for human drug and blood products mandated that manufacturers print a barcode (one dimensional) on every product at the unit of use addressing the issue of lack of unique identifiers and suggesting the use of either GS1 or HIBCC standards.
- In September 27 2007, the FDA Amendments Act of 2007 was signed into law; this Act includes the establishment of a unique device identification system. This new system when implemented will require the label of a device to bear a unique identifier. This unique identifier must be able to identify the device through distribution and use.
- In 2008 (25 years after the first attempt) an industry movement towards GS1 standards system adoption was initiated. Currently the industry is building consensus regarding the adoption of GS1 standards.

Results from pilot projects developed at the Department of Defense (DoD) which go back to 1995 have demonstrated the benefits of a Product Data Utility (PDU) and unique identifiers such as the UPN. The current DoD pilot project is testing the GS1 Global Data Synchronization Network (GDSN) as a PDU for healthcare industry using the Global Trade Identification Numbers (GTIN) as the unique identifier for products flowing through the healthcare supply chain. The industry established deadlines for the adoption of the different standards; the deadline for the location identifiers adoption was December 31st of 2010 and the deadline of the product identifiers adoption is December 31st of 2012.

1.3 Research Problem

The adoption of identification standards and it associated technology in the healthcare supply chain has been slow over the past twenty five years despite empirical evidence of the benefits that can be achieved. The first movement towards identification standards adoption was initiated

in the year 1983 as referenced by (HIMSS, 2003). The EHCR initiative (CSC, 1996) identified in 1996 more than six billion in potential savings for barcode technology use within the hospital supply chain. Today, more than twenty five years after the first attempt to identification standards adoption, the standards are not widely adopted and the benefits are still to be realized. This slow adoption process is preventing the healthcare supply chain from reaching the benefits and process efficiencies other industries have realized, and, most importantly, it is affecting the healthcare delivery process since identification standards are known to be useful on preventing medical errors (e.g. wrong dose to right patient, right dose to wrong patient) and facilitating the recall process of pharmaceuticals, medical supplies and devices.

As reported by (Simpson & Kleinberg, 2009) the main contributors for the slow adoption include market drivers and technology issues. There is a major "chicken versus egg" problem on unit of use bar coding (i.e printing a barcode label at the smallest unit of use on every pharmaceutical and medical supply). Initially manufacturers were unwilling to barcode their products since they knew the hospitals did not have the scanners to read them and hospitals were reluctant to invest in barcode scanning technology if the products did not come labeled with barcodes. In the technology side, major healthcare information systems vendors have lagged behind in providing robust barcode enabled applications to support supply chain processes.

1.3.1 Research questions

The main research questions to be addressed with this research project are the following:

1. How does the identification standards adoption process compare with the same or similar adoption process in other industries such as retail?

2. How does the identification standards adoption and diffusion process compare with the adoption of other technologies within the healthcare industry in general. (e.g. the diffusion of medical technologies or Electronic Health Records EHR)?
3. What is preventing healthcare supply chain members and healthcare providers in particular from adopting identification standards and it supporting technologies? What are the major barriers?
4. How could existing diffusion models be extended or modified to model the healthcare identification standards adoption process?
5. What are the cost implications and benefits for the healthcare supply chain members and stakeholders to adopt identification standards?
6. What actions (strategies, incentives and policies) are required to increase the number of healthcare supply chain members and healthcare providers adopting identification standards?

In order to answer the proposed research questions, this research is divided in two phases. Phase I is related to questions 1, 2 and 3. Phase II is related to questions 4, 5 and 6. Each phase develops a main objectives and a main hypothesis as explained in the following paragraphs.

Phase I

Main objective. To identify the main barriers affecting the data standards adoption process (research question number 3) in order to explain the adoption process from the technology adoption perspective, and to develop a conceptual model.

Main hypothesis. The identification standards adoption process can be understood, explained and improved with information related to similar adoption processes within and outside of the healthcare domain.

Phase II

Main objective. To develop a theoretical model to investigate the dynamics of the adoption of identification standards in the U.S healthcare supply chain (research question number 4). The model will be based on the diffusion of innovations theory; a systems dynamics modeling approach will be used to model this process.

Main hypothesis. Technology diffusion models can help to explain and model the adoption of identification standards. Classic diffusion models can be extended to model identification standards adoption; the developed model will facilitate the understanding of the system (healthcare supply chain) behavior and allows for the design and test of policies to move the system forward.

1.3.2 Methodology

Phase I

An extensive literature review followed by a comparative analysis is the methodology to be used to answer the research questions related to this phase. An extensive review of the literature on data standards adoption, healthcare and non healthcare related adoption processes is developed. The most relevant conceptual models for factor identification and adoption modeling are explained. The literature review provides the necessary information to identify the factors that are affecting the identification standards adoption process, a conceptual model is proposed.

Phase II

The second phase is related to the model development and is based on the system dynamics methodology. As defined by (Coyle, 1983), system dynamics is a rigorous method of system description, which facilitates feedback analysis, usually via a continuous simulation model of the effects of alternative system structures and control policies on system behavior.

As implied by the system dynamics methodology, the purpose of a model is to understand the structure of the system and to provide insights into the possible solutions to the existing problems.

The basic steps of the system dynamics methodology are the following:

- Definition of the real world symptoms to be understood and improved
- System description by the use of a Causal Loop Diagram
- Model formulation
- Model verification and validation
- Simulation experiments, leading to improved understanding on the problem underlying the symptoms
- Redesign and implement change on system structures or policies in order to improve its dynamic behavior

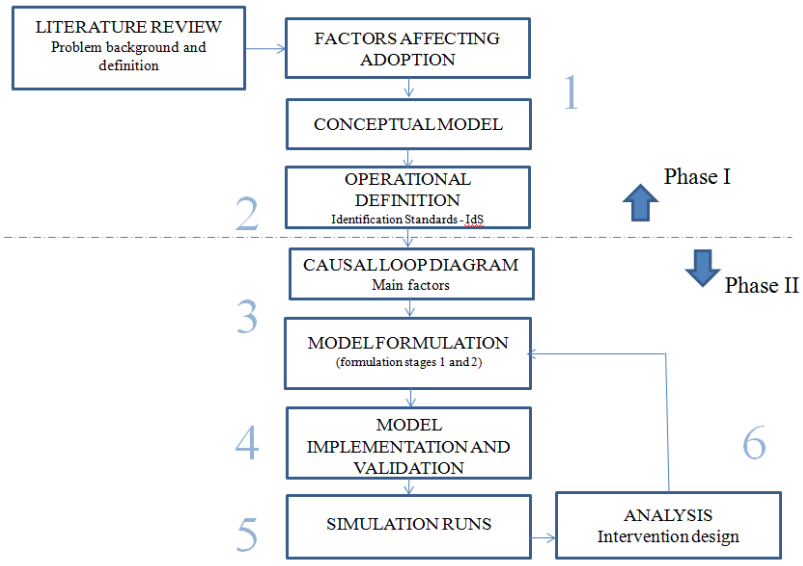

Figure 3. Research methodology

The complete research methodology including Phases I and II is summarized in Figure 3.

1.3.3 Summary of expected contributions

The expected contributions from this research include the following: (1) Categorization of data standards related literature, (2) Conceptual model to explain barriers to adoption, (3) Diffusion model formulation and resulting simulation model, and (4) Model extensions to include cost and benefits estimations and policy related considerations.

Contributions from Phase I: Identification of the major barriers affecting the identification standards adoption process:

- Identification and classification of documents related to technology adoption and diffusion within the healthcare domain, characterization of main adoption process.
- Identification and classification of documents related to technology adoption and diffusion outside the healthcare domain, characterization of main adoption process.

- Identification and classification of documents related to data standards adoption.
- Comparative analysis of findings and development of a conceptual model to explain data standards adoption.

Contributions from Phase II: Development and implementation of a modeling approach for data standards adoption:

- Identification and classification of documents related to technology adoption modeling within and outside the healthcare domains, identification of main methods.
- Diffusion model formulation to model data standards adoption.
- Simulation model implementation and experimentation.
- Model extensions to include the cost and benefits estimations and policy interventions.

1.3.4 Research importance

The study of the data standards adoption process provides an opportunity to enhance the understanding of the adoption process by exploring related adoption processes that could lead to the analysis from an academic perspective of previous failed data standards adoption attempts. A similar standards movement was started in 1983 with no successful outcome.

Technology adoption and diffusion are important challenges as revealed by (Sheng, R., Jen Hwa, Wei, Higa, & A., 1998). The adoption and diffusion of technology within healthcare is important since its widespread use can contribute to the reduction of costs, through the increase of efficiency and most important improvements in patient safety (Kohn, Corrigan, & Donaldson, 2000).

1.4 Dissertation document structure

This document is divided into six chapters. The background information, the description of the research problem, the research questions along with the description of the methodology are introduced in Chapter 1. A literature review, related to non-healthcare and healthcare related adoption processes, is presented in Chapter 2. In this chapter the findings related to the main conceptual models and adoption determinants are explained. The literature review related to data standards literature with specific focus on barriers is presented in Chapter 3 along with the development of the proposed conceptual model to explain the identification standards adoption process. The model formulation and development is presented in Chapter 4, this chapter includes the development of the causal loop diagram along with the proposed formulation stages. The model implementation, sensitivity analysis and interventions design is presented in Chapter 5. The conclusions and future work are presented in Chapter 6.

2. Literature Review

The goal of this chapter is to answer the following research questions as established in Chapter 1:

- *How does the identification standards adoption process compare with the same adoption process in other industries such as retail?*
- *How does the identification standards adoption and diffusion process compare with the adoption of other technologies within the healthcare industry in general (e.g. the diffusion of medical technologies or Electronic Health Records EHR)?*

The characterization of a main adoption process within the non healthcare and healthcare domains was established. A literature review was conducted in order to achieve that goal. The main findings of the literature review are presented in this chapter. The comparison of the identification standards adoption process and healthcare and non healthcare adoption processes is developed in Chapter 3.

The Management of Technology (MOT) approach (Gaimon, 2008), is defined as a key element of the literature review. Under this approach researchers attempt to explain a given adoption process by defining conceptual models that could lead to generalizations. Since the goal if this research is to understand the identification standards adoption process the MOT approach was found suitable for this purpose. In this research it was assumed that findings related to specific adoption processes could help to understand the identification standards adoption process under study. Adoption processes within the healthcare and non healthcare domains were explored.

For non healthcare related adoption processes, the initial technology used in the search was Electronic Data Interchange (EDI). For healthcare related adoption processes, the search started by focusing on the adoption of Electronic Health Records (EHR). The search was conducted using various search engines such as Engineering Village, EBSCO and Pro Quest. In order to start the search the terms EDI and EHR were used. For Engineering Village data base the terms EDI and EHR plus the term *adoption* and *United States* as a location element to conduct the search were used. The starting date for the search was 1980; the goal was to include the research work developed over the past three decades. For the Pro Quest and EBSCO databases the search was conducted with the terms EDI and EHR plus *adoption, conceptual model* and *mathematical model* using the same date range and location parameters. The initial goal was to keep the search just for US adoption processes but some outside cases were considered. As a result 85 documents were reviewed (title and abstract) and reduced to 41 documents divided in two categories. Category 1, non-healthcare related documents and category 2, healthcare related documents as shown in Tables 1 and 2.

For both categories the documents were classified in the following document types: Journal (J), Dissertation (D), Book chapter (B), Conference proceedings (C) and Report (R). In total, there are 27 Journals, 3 Dissertations, 3 Book chapters, 3 Conference proceedings and 5 Reports. The journals are mainly from the areas of information systems (12), decision sciences (4) and engineering management fields (4), and the remaining (7) belong to healthcare related publications.

Table 1. Category 1 literature review

Technology		References	Year	Journal / source	Type	Focus	Country
IOS	1	Alexander	1989	Unpublished Ph.D. Dissertation, Indiana University	D	DBM	US
	2	Hoffer et al	1992	Data Base	J	DBM	US
	3	Grover	1993	Decision Sciences	J	CIOS	US
	4	Vlosky et al	1994	Report, IBMPS	R	Retail IO	US
	5	Nelson	2003	Unpublished Ph.D. Dissertation	D	IOS	US
EDI	6	Ramamurthy et al	1995	IEEE Transactions on Engineering Management	J	Large firms	US
	7	Iacovou et al	1995	MIS Quarterly	J	SMB	US
	8	Arunachalan	1995	Journal of Systems Management	J	EDI users	US
	9	McGowan and Madey a	1998	Information Resources Management Journal	J	EDI users	US
	10	McGowan and Madey b	1998	Information Systems Innovation and Diffusion	B	EDI	US
	11	Niederman	1998	Information Systems Innovation and Diffusion	B	EDI	US
	12	Palmer	1998	Information Systems Innovation and Diffusion	B	EDI	US
	13	Iskandar et al	2001	IEEE Transactions on Engineering Management	J	Automotive	US
	14	Kuan et al	2001	Information & Management	J	SMB	Hong Kong
	15	Narayanan et al	2009	Decision Sciences	J	EDI	US
MRP / ERP	16	Cooper and Zmud	1990	Management Science	J	MRP	US
	17	Kerimoglu et al	2008	Journal of High Technology Management Research	J	ERP	Turkey
Others	18	Zhu et al	2006	Management Science	J	e-business	10 countries
	19	Hwang et al	2009	Telecommunications Policy	J	M -phones	Vietnam
	20	Quan et al	2010	Journal of Computers	J	M-service	China
	21	Hossain	2008	IEEE Transactions on Engineering Management	J	RFID	Bangladesh

Table 2. Category 2 literature review

Technology		References	Year	Journal / source	Type	Focus	Country
Medical technology	1	Greer	1985	Intl. journal of technology assessment in health care	J	12 technologies	US
Assisting technology	2	Sheng et al	1998	Journal of Organizational Computing	J	Telemedicine	Hong Kong
	3	Paul et al	1999	IEEE Transactions on Engineering Management	J	Telemedicine	US
	4	Hung et al	2009	Decision Support System	J	CRM	Taiwan
EHR	5	Miller and Sim	2004	Health Affairs	J	EMR	US
	6	Ash and Bates	2005	Journal of the American Medical Informatics Association	J	EHR	US
	7	Middleton et al	2005	Journal of the American Medical Informatics Association	J	EHR	US
	8	Woodside	2007	JHIM HIMSS	J	EHR	US
	9	Chang et al	2007	Decision Support System	J	e-signature	Taiwan
	10	Erdil	2008	SD 2008 Conference proceedings	C	EHR	US
	11	Erdil a	2009	SD 2009 Conference proceedings	C	EHR	US
	12	Erdil b	2009	Unpublished Ph.D Dissertation	D	EHR	US
HIT / EHR	13	Hillestad et al	2005	Health Affairs	J	HIT / EMR	US
	14	Shortliffe	2005	Health Affairs	J	HIT	US
	15	Bower	2005	RAND report	R	HIT/EHR	US
	16	Fonkych and Taylor	2005	RAND report	R	HIT	US
	17	Girosi et al	2005	RAND report	R	HIT/EHR	US
	18	Conklin et al	2009	RAND report	R	RFID	Europe
	19	Daim et al	2008	Proceedings of the 41st Hawaii Intl. Conference on System Sciences	C	HIT	US
	20	Daim et al	2009	Int. Journal of Behavioural and Healthcare Research	J	PHR	US

2.1 Category 1 (Non Healthcare)

The documents (21) were fully reviewed and classified according to the year of publication, document type and focus. Among the non-healthcare related adoption documents the following technologies were identified: Inter Organizational Systems (IOS), Electronic Data Interchange (EDI), Manufacturing Resource Planning (MRP), Enterprise Resource Planning (ERP) and a category of others. The documents were also reviewed according to the scope, modeling approach and factor identification methods. The date range was from the year 1989 to the year 2010. The summary of the documents within category one is shown in Table 1.

2.2.1 IOS

The study of Inter Organizational Systems (IOS) was initiated with the work of (Alexander, The Adoption and Implementation of Computer Technology in Organizations: The Example of Database Machines, 1989) and (Grover, 1993). In his work (Alexander, The Adoption and Implementation of Computer Technology in Organizations: The Example of Database Machines, 1989) the author developed a conceptual model in order to explain the adoption and implementation of Data Base Machines (DBM). This work considered the organizational perspective and was based on Diffusion of Innovations (DOI) theory. The sample size of the survey was expanded by (Hoffer & Alexander, 1992). The authors proposed ten factors are related to the implementation of database machines those were: compatibility, relative advantage, complexity, training, vendor involvement, organization structure, management support, planning, champions and awareness of technology. In a more generic way (Grover, 1993) developed a conceptual model to explain the adoption of Customer-based Inter

Organizational Systems (CIOS). This conceptual model was tested with a sample of industry leaders. Among the main findings was the development of a composite model which included organizational factors, policy factors, environmental factors and technology specific factors; and the identification of a proactive technological orientation and the internal push for the system as the two most relevant factors affecting adoption.

The adoption of IOS was also studied by (Volsky & Wilson, 1994) using the relationship between a buyer and a seller in the retail context. The model developed four hypotheses which were tested with a survey. Among the most relevant findings was the fact that channel relationship deterioration occurs during the early stages of IOS technology adoption, mainly due to the low value perceived relative to the investments made by the parties involved.

The adoption and diffusion of Inter Organizational System standards and process innovations was studied by (Nelson, 2003). The author developed a conceptual model which linked the adoption and diffusion (deployment) to three main constructs which are organizational, technology and environment factors. The author found a difference between the factors affecting adoption and the factors affecting deployment.

2.1.2 EDI

The results of a survey on the use of EDI among 900 firms were presented by (Arunachalam, 1995). The survey identified the main reasons for adopting EDI, the perceived barriers and realized benefits. According to the survey some of the main reasons to adopt EDI were: to remain competitive, customer's request, provide better customer service and to reduce paperwork. The perceived barriers were related to the lack of awareness of EDI benefits, lack of

automation, high costs and training. According to the survey, most customers were able to improve customer service and reduce transaction errors. In the same way, the work developed by (Ramamurthy & Premkumar, 1995) introduced a conceptual model based on DOI to explain the implementation of EDI in large firms and its impact on the business performance. The results from testing the conceptual model among industry leaders in the form of a survey indicated that the greater internal and external diffusion of EDI facilitated the achievement of improved organizational outcomes. The work of (Iacovou, Benbasat, & Dexter, 1995) presented a conceptual model to study the EDI adoption on small and medium businesses. This model described the effect of three explanatory factors (perceived benefits, organizational readiness and external pressure) on the adoption of EDI. The authors tested the model with the use of case studies and recommended the establishment of a long term EDI partner expansion plan and the individual assessment of each partner preparedness level, as key elements in the adoption process.

Similarly, the work of (McGowan & Madey, Adoption and implementation of Electronic Data Interchange, 1998) started with the definition of a conceptual model for EDI adoption and implementation based on DOI using a case study approach; four organizations were studied. The results of the study suggested that the factors that influence the adoption decision might be different from the factors influencing the extent of the EDI implementation within the organization. Among one of the main factors affecting the adoption was the customer influence. On a subsequent work (McGowan & Madey, The influence of organization structure and organizational learning factors on the extent of EDI implementation in U.S. firms, 1998) developed a survey to establish the aspects related to the EDI implementation and diffusion within the organization. The EDI implementation extent was assessed through the volume,

diversity and sophistication of EDI use within the organization. The results showed that the size of the organization explains much of the extent of EDI implementation which could be related to resource availability. The EDI adoption was reviewed by (Niederman, 1998) from the diffusion of innovations perspective and the author suggested the introduction of risk and critical mass as factors to be considered when analyzing technology adoption. The conceptual model developed by (Palmer, 1998) was used to study the adoption and diffusion of EDI under a quick response strategy. The study findings suggested that the factors affecting the adoption might be different from the factors affecting implementation. Firm size was confirmed as a key factor affecting adoption, however, the results regarding implementation were inconclusive.

The adoption and integration of EDI within the automotive industry was studied by (Iskandar, Kurokawa, & LeBlanc, 2001), the authors proposed a conceptual model and developed a survey in order to gather information to test the proposed hypothesis. The results from the study indicated that the factors affecting the adoption are different from the factors affecting the implementation even though both can be considered simultaneously taking into consideration a short implementation period.

The work developed by (Kuan & Patrick, 2001) included the development of a conceptual model to study the adoption of EDI among small and medium businesses. The proposed conceptual model was based on the Technology, Organization, and Environment (TOE) model previously developed by (Tornatzky & Fleisher, 1990). The model differentiated among adopters and non adopters. Some of the main findings included the fact that direct benefits were perceived to be higher by adopter firms compared to non-adopter firms and the indirect benefits did not reveal any difference among the two groups. The work developed by (Narayanan, Marucheck, &

Handfield, 2009) summarized the findings on EDI adoption and implementation research over the past 20 years. The study synthesized the EDI literature and with the development of a meta-analysis of findings, the authors were able to clarify some conflicting results regarding EDI adoption and implementation benefits. In this paper the authors established that no unified model exist to analyze the adoption and implementation of EDI. No agreement on results from adoption and implementation has been reached and most of the results related to the estimation of the benefits are inconclusive.

2.1.3 MRP/ERP

(Cooper & Zmud, 1990) studied the adoption and implementation of Manufacturing Resource Planning (MRP) systems and indicated that the factors affecting the adoption are different from the factors affecting the internal implementation or infusion, as also noted by (Palmer, 1998) (Iskandar, Kurokawa, & LeBlanc, 2001) regarding EDI. The adoption of Enterprise Resource Planning (ERP) systems from the end user perspective was studied by (Kerimoglu, Basoglu, & Daim, 2008) and the authors constructed a model based on the Technology Acceptance Model (TAM) developed by (Davis, Bagozzi, & Warshaw, 1989). Results from the study indicated that organizational adoption can be achieved if the end user satisfaction is achieved; there were also indications of special project management efforts during the implementation phase that can contribute to end user satisfaction.

2.1.4 Others

The adoption of electronic business was studied by (Zhu, Kraemer, & Xu, 2006). The authors developed a three stage model including the phases of: initiation, adoption and routinization. The

model was based on the TOE model (Tornatzky & Fleisher, 1990) and some of the findings indicated that competition positively affects adoption and initiation, and that resource availability had an impact on initiation. The analysis of the telecommunication services in Vietnam was performed by (Hwang, Cho, & Long, 2009) with the use of a diffusion model. The findings of the model implementation suggested that a regulation that could guarantee competition could be a factor to positively influence the diffusion process. An extension of TAM (Davis, Bagozzi, & Warshaw, 1989) was developed by (Quan, Hao, & Jianxin, 2010) in order to study the adoption of mobile services. The authors did so by introducing the perceived credibility and perceived constructs into the model. The adoption of RFID from the end user perspective was studied by (Hossain & Prybutok, 2008), the authors developed a model based on TAM and proposed that convenience, culture, privacy, regulation and security were important factors related to the RFID adoption among end users.

2.1.5 Conceptual models elements and mathematical modeling (specific findings)

A conceptual model was identified in 17 documents as shown in Table 3. The most widely used technique to test a proposed conceptual model and its related hypothesis was a survey or industry panel. The main adopting unit (U) referenced in most of the documents is the organization (O) in contrast to the end user perspective (E). There are 9 documents related to both adoption and implementation, 9 documents with a specific focus on adoption and 2 dealing with only implementation. The exploration of the benefits (B) was found in 5 documents. There is one document related to the development of a mathematical diffusion model. The summary of the findings is presented in Table 3.

For the conceptual models the dominant approach is the Diffusion of Innovations (DOI), about half of the identified documents used that approach. The Technology, Organization and Environment (TOE) model was also present, both DOI and TOE are used to analyze the adoption from the organizational point of view, as in the case of database machines, EDI, MRP and electronic business. The Technology Acceptance Model (TAM) was used to study the adoption of technology from the end user perspective as in the case of ERP, RFID and mobile services.

The realization of the benefits comes after the implementation phase. As described by (Narayanan, Marucheck, & Handfield, 2009) , (McGowan & Madey, Adoption and implementation of Electronic Data Interchange, 1998), (Nelson, 2003) there is a difference between the factors affecting adoption and the factors related to the implementation. In general, the adoption phase is the early stage of the adoption process while the implementation requires the continued use of the technology within the organization.

Table 3. Category 1 findings

Tech.		References	Year	Approach / Method	Scope	U	A	I	A & I	B	Conceptual model	Math.
IOS	1	Alexander	1989	Lit. review + survey	143(60.8% rr)	O	x	x	x		DOI	N
	2	Hoffer et al	1992	Lit. review + survey	142(47 ans.s)	O	x	x	x		DOI	N
	3	Grover	1993	Lit. review + survey	1069(21.14%rr)	O	**x**				DOI	N
	4	Vlosky et al*	1994	Survey	540 (227 ans.)	O	**x**				None	N
	5	Nelson	2003	Lit. review + survey	590 (102 ans.)	O	x	x	x		TOE	N
EDI	6	Ramamurthy et al	1995	Lit. review + survey	1200 (17% rr)	O		**x**		x	DOI	N
	7	Iacovou et al	1995	Case studies	7 case studies	O	x	x	x	x	general	N
	8	Arunachalan*	1995	Lit. review + survey	900(180 ans.)	O				x	None	N
	9	McGowan and Madey a	1998	Lit. review + survey	1200 (22,17% rr)	O		**x**			DOI	N
	10	McGowan and Madey b	1998	Lit. review+ case studies	4 sites	O	**x**				DOI	N
	11	Niederman	1998	Lit. review	review paper	O	**x**			x	None	N
	12	Palmer	1998	Lit. review + case studies	175(45.7% rr)	O	x	x	x		DOI	N
	13	Iskandar et al	2001	Qualitative / Survey	547(24% rr)	O	x	x	x		general	N
	14	Kuan et al	2001	Literature review	575 firms	O	**x**				TOE	N
	15	Narayanan et al	2009	Literature review	Literature review	O	x	x	x	x	general	N
MRP / ERP	16	Cooper and Zmud	1990	Lit. review + survey	52 firms	O	x	x	x		general	N
	17	Kerimoglu et al	2008	Lit. review + survey	223 (585 rr)	E	**x**				TAM	N
Others	18	Zhu et al	2006	Lit. review + survey	1857 firms	O	x	x	x		TOE	N
	19	Hwang et al	2009	Literature review	Dataset 1995-2006	E	**x**				None	Y
	20	Quan et al	2010	Lit. review + survey	228 surveys	E	**x**				TAM	N
	21	Hossain	2008	Lit. review + survey	307(83.4%rr)	E	**x**				TAM	N

* barrier related

According to the mathematical models explored, (Hwang, Cho, & Long, 2009) developed a diffusion model to investigate the factors affecting the diffusion of mobile telephone services in Vietnam. The logistic regression model was found to perform better as a descriptive tool for the period under study (1995-2006) and it was used to determine the factors affecting the speed of diffusion. The findings suggest that a regulation that could guarantee competition in the market is one of the most important factors for a positive diffusion process.

2.2 Category 2 (Healthcare)

There were 20 healthcare related adoption documents in total. The documents were fully reviewed and classified according to the document type and focus. The healthcare related documents were grouped in the following categories: medical technology, assisting technology, Electronic Health Records (EHR) and Health Information Technology (HIT). The documents were also reviewed according to the scope, modeling approach and factor identification methods; most of the documents were within the present decade. The summary of the documents within category two is shown in Table 2.

2.2.1 Medical technology

The work developed by (Greer, 1985) reported on the findings of the analysis of adoption of 12 medical technologies among 25 healthcare institutions. The author found that within the explored healthcare institutions there were three decision systems involved in the adoption decision (medical-individualistic, fiscal-managerial and strategic-institutional). With the use of case studies the author found that each technology was related to a specific system. This finding highlights the importance of establishing the distinction among technologies in order to analyze

the adoption process. For example there are technologies that require the end user (physician) to be comfortable to use, while others that could serve the purpose of improving the efficiency of a given department do not require physician involvement; then a different system would be considered in the decision process.

2.2.2 Assisting technology

In the case of telemedicine, (Paul, Pearlson, & McDaniel, 1999) explored the technological barriers to its adoption by the use of case studies. The authors found that end user training was one of the most relevant barriers. The work developed by (Sheng, R., Jen Hwa, Wei, Higa, & A., 1998) introduced a conceptual model for the internal adoption of telemedicine and described the individual-organizational space in which the adoption takes place. The adoption of Customer Relationship Management (CRM) systems in the hospital setting was studied by (Hung, Hung, Tsai, & Jian, 2009) the authors proposed a conceptual model based on TOE (Tornatzky & Fleisher, 1990) and found that hospital size, capabilities of staff, innovation of senior executives, knowledge management capabilities and relative advantage have significant influence on CRM systems adoption.

2.2.3 Electronic Health Records - EHR

The study developed by (Miller & Sim, 2004) focused on the identification of barriers to EHR adoption among physicians. The study was based on interviews with healthcare professionals. Among the identified barriers are the high initial cost, uncertain financial benefits, inadequate support and lack of incentives. According to (Ash & Bates, 2005) the barriers to Computarized Physician Order Entry (CPOE) can be grouped in four factors, organizational, technical,

environmental and end user related. Among the recommendations to promote EHR adoption, (Middleton, Hammond, Brenan, & Cooper, 2005) discussed five options, expand the Health Information Technology HIT research agenda, establish financial benefits to stimulate the EHR marketplace, coordinate HIT standards development, establish enabling policy and promote educational activities.

The research conducted by (Chang, Hwang, Hung, Lin, & Yen, 2007) studied the adoption of electronic signature among hospitals and developed a conceptual model based on TOE. The authors reported that there are four significant factors that distinguish adopters from non adopters: hospital size, adequate resources, vendor support and government policy.

(Woodside, 2007) developed a model based on game theory to explain the EHR adoption. In this model the author assumed the EHR adoption as a zero sum game with three players, the payer, the healthcare provider and the consumer; all players were assumed to act rationally which means all players tended to maximize their payoffs. The model identified the payoffs for each player as well as the stages of the game in order to reach equilibrium or recommended path. Two equilibriums were reached during the game. The first one, when the payer subsidizes the provider to the extent that it is profitable and the second one, when the payer subsidizes the provider indirectly through the consumer, to the extent that it is profitable.

The research developed by (Erdil & Emerson, Modeling the dynamics of Electronic Health Records adoption in the U.S healthcare system, 2008) was related to the study of EHR adoption. The research started with the identification of the barriers to EHR adoption in the form of a causal loop diagram. The causal loop diagram captured the cause and effect relationship in the form of feedback loops amongst the factors influencing the EHR adoption process. Then, the

structure of the causal loop diagram is used to construct a model to simulate the hospital's EHR adoption rate over time (Erdil & Emerson, Simulation modeling of electronic health records adoption in the U.S healthcare system, 2009). Cost was identified as one of the main factors affecting adoption. The details of the model development and preliminary findings are presented in the dissertation (Erdil, Systems analysis of Electronic Health Record adoption in the U.S. healthcare system, 2009).

2.2.4 Health Information Technology - HIT

The work developed by RAND Corporation on the adoption of Health Information Technology HIT was associated in particular to the adoption of HIT in the context of Electronic Health Records. As reported by (Bower, The Diffusion and Value of Healthcare Information Technology, 2005) the penetration of EHR can be approximated by measuring the number of hospitals having a set of applications such as clinical decision support systems, computerized patient records and a clinical data repository. Using that definition the author was able to establish that the penetration of EHR by the year 2002 was about 32%. An assessment of causal diffusion variables was developed and seven variables were identified: relative advantage to clinicians, compatibility, complexity, external influence, social pressure, network effects and specialization. The potential value of system wide HIT diffusion was estimated by defining different scenarios for productivity gains related to EHR adoption. The intervention of the government in order to speed up diffusion was also discussed. The analysis of the pattern of HIT adoption among for profit and non for profit hospitals was developed by (Fonkych & Taylor, 2005), the report findings suggest there is high heterogeneity in HIT adoption across HIT applications and types of hospitals.

The report by (Girosi, Meili, & Scoville, 2005) identified the cost and benefits of HIT. The potential health and financial benefits of health information technology HIT adoption were examined by (Hillestad, et al., 2005). In order to do that, a comparison of the use of IT in healthcare with the use of IT in other industries was developed; additionally the potential savings and costs of widespread adoption of Electronic Medical Record (EMR) systems were estimated. The authors concluded that effective EMR implementation could save more than 81 billion annually by improving health care efficiency and safety. Some of the identified factors affecting adoption were: the high starting and implementation costs, the slow and uncertain payoffs and the disruption of current practice. The work developed by (Shortliffe, 2005) described the current opportunities and challenges of medical records automation; among the challenges, cultural barriers, business case absence and structural barriers were identified.

Another HIT report by RAND Corporation (Oranje-Nassau, Schindler, Valeri, Vilamovska, Hatziandreau, & Conklin, 2009) commented on the identification of drivers and barriers of RFID adoption in healthcare. Among the main barriers to RFID adoption are organizational issues such as change management and end user resistance; technical issues such as scalability, integration and market maturity; and security and privacy issues such as data integrity and reliability.

The work by (Daim, Tarman, & Basoglu, Exploring Barriers to Innovation Diffusion in Healthcare Service Organizations: An issue for effective integration of service architecture and information technologies, 2008) focused on HIT adoption in general. The main barriers to adoption were identified through a literature review and an initial conceptual model was proposed. The assessment of the barriers related to Personal Health Records adoption (PHR)

were explored by (Daim, Chan, Amer, & Aldhaban, 2009), this assessment was developed using the TAM conceptual model.

2.2.5 Conceptual model elements and mathematical modeling (specific findings)

A conceptual model was identified within 6 documents. There were 7 documents associated to the identification of barriers. There were 4 documents related to the estimation of the benefits, most of those are RAND reports, based on the estimation of the value of HIT and EHR in particular. The summary of the findings is presented in Table 4. Among the conceptual models there was no dominant approach. The unit of analysis in the case of healthcare related technology adoption processes included the end user (E), which could be the physician or the nurse. The end user perspective was not present in the non-healthcare related technology adoption (IOS/EDI) documents. The adoption and implementation studies (5) were found in the review but there were no specific studies related to the specific implementation phase. This issue can be associated to the lack of studies linked to the estimation of the benefits of EHR adoption. This can be an indication of the early stage of this adoption process according to the phases defined by Rogers (Rogers E. M., 1983).

The two specific mathematical modeling efforts are summarized in the work developed by (Erdil, Systems analysis of Electronic Health Record adoption in the U.S. healthcare system, 2009) and (Woodside, 2007). These authors explored the use of game theory and system dynamics modeling to understand the EHR adoption process.

2.3 Theoretical findings

2.3.1 Technology adoption conceptual models

The documents referenced in this section belong to the group of 23 documents associated to specific conceptual models as shown in Tables 3 and 4. There were 17 documents related to a conceptual model within the category 1 reviewed documents and there were 6 documents related to a conceptual model within the category 2 reviewed documents. The main conceptual models identified through the literature review were Diffusion of Innovations (DOI), Technology Organization and Environment (TOE) model and Technology Acceptance Model (TAM).

DOI

The work initiated by (Rogers, Diffusion of Innovations, 1983) developed most of the foundation for the diffusion of innovations approach. The author defined the different adoption stages and how the characteristics of the innovation influence the adoption process. The adoption stages are illustrated in Figure 4. According to (Rogers, Diffusion of Innovations, 1983), there are different factors affecting the adoption rate. Those factors are mostly related to the characteristics of the technology and the most relevant ones include: relative advantage, complexity and compatibility. This conceptual model was present in 8 of the 23 documents included in the analysis of conceptual models.

Table 4. Category 2 Findings

Technology		References	Year	Focus	Approach / Method	U	A	I	A& I	B	Conceptual model	Math.
Medical technology	1	Greer	1985	12 technologies	Case studies	O	x				None	N
Assisting technology	2	Sheng et al	1998	Telem.	Case studies	E,O	x	x	x		General	N
	3	Paul et al*	1999	Telem.	Site visits + interv.	O	x				None	N
	4	Hung et al	2009	CRM	Surveys + H. testing	O	x				TOE	N
EHR	5	Miller and Sim*	2004	EMR	Experts opinion	E,O	x				None	N
	6	Ash and Bates*	2005	EHR	Experts opinion	O	x				None	N
	7	Middleton et al	2005	EHR	Experts opinion	O	x				None	N
	8	Woodside	2007	EHR	Model	O	x	x	x		None	Y
	9	Chang et al	2007	e-sign.	Lit. review + surveys	O	x				TOE	N
	10	Erdil*	2008	EHR	Lit. review	O	x				None	N
	11	Erdil a	2009	EHR	Lit. review	O	x	x	x		None	Y
	12	Erdil b	2009	EHR	Lit. review + survey	O	x				None	Y
HIT/ EHR	13	Hillestad et al	2005	HIT / EMR	Report summary	O	x	x	x	x	None	N
	14	Shortliffe*	2005	HIT	Lit. review + opinion	O	x				None	N
	15	Bower	2005	HIT/EHR	Lit. review + interv.	O	x			x	DOI	N
	16	Fonkych and Taylor*	2005	HIT	Report summary	O	x				None	N
	17	Girosi et al	2005	HIT/EHR	Report summary	O	x	x	x	x	None	N
	18	Conklin et al*	2009	RFID	Lit. review + interv.	O	x			x	None	N
	19	Daim et al	2008	HIT	Lit. review + interv.	O	x				TAM	N
	20	Daim et al	2009	PHR	Lit.review + survey	E	x				TAM	N

* barrier related document

According to (Niederman, 1998) the first goal of diffusion theory is to develop a general understanding of individual and organizational reactions to the introduction of new technologies. This general understanding includes the identification of factors that can influence the processes or outcomes of the innovation project to varying degrees under varying circumstances. The second goal of diffusion theory is to provide a method of analyzing the characteristics of a proposed new technology in order to forecast likely patterns of diffusion within and or outside the organization as well as to anticipate problems and intervene in positive ways to overcome these problems. The analysis of an adoption process requires the definition of a unit of adoption or perspective.

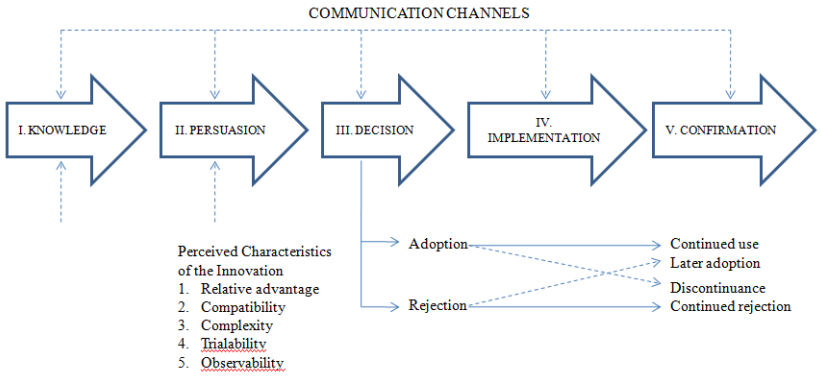

Figure 4. Adoption stages (adapted from Rogers, 1983)

From the DOI perspective the unit of adoption can be defined as the end user (E) or the organization (O). The work developed by (Wolfe, 1994) introduced the concept of organizational innovation and presented a conceptual model for its understanding.

TOE

The Technology, Organization, Environment (TOE) model was proposed by (Tornatzky & Fleisher, 1990) in order to explain the factors that influence an organization's adoption process. This conceptual model is consistent with (Rogers, Diffusion of Innovations, 1983) theory of innovation adoption but adds the organizational and environment factors to the analysis of the adoption process. Under the DOI approach the factors affecting the adoption can be related to the characteristics of the technology, however there are other factors to be considered such as organization and external related factors. This model was present in 5 of the 23 documents related to conceptual models. The TOE conceptual model (Tornatzky & Fleisher, 1990) has been examined by a number of empirical studies on technology adoption, in particular on the adoption of EDI.

TAM

The Technology Acceptance Model (TAM) (Davis, Bagozzi, & Warshaw, 1989) is used to explain the adoption of technology from the end user perspective. According to TAM there are two key determinants of end user adoption; those are the perceived usefulness and the perceived ease of use. The perceived usefulness is defined as the degree to which a person believes that using a particular technology would increase his or her job performance, while the perceived ease of use is defined as the degree to which the end user expects the technology to be free of effort. The model provides strong empirical evidence on the contribution of these two variables in the end user adoption decision. This conceptual model has been widely applied to explain different end user related innovations, such as the adoption of Personal Health Records (PHR)

and ERP systems. There are 5 of the 23 documents related to conceptual models using this approach.

2.3.2 Mathematical models

From the complete set of reviewed documents (41), 4 documents are related to a mathematical modeling approach. Those are described in the following paragraphs.

Diffusion curves

The research developed by (Teng, Grover, & Guttler, 2002) on diffusion curves and mathematical modeling provided evidence of the relationship between factors affecting a diffusion process and the diffusion pattern. The authors used adoption related data from 21 technologies and established that the mixed influence diffusion model was one of the models that best fit the available data. Based on that information, a classification of the different technologies was made by using some of the parameters of the model.

Game theory

The adoption of EHR was explained by (Woodside, 2007), this work illustrated game theory as a modeling approach for EHR. In this model the author assumed the EHR adoption as a zero sum game with three players: the payer, the healthcare provider and the consumer. In the game all players were assumed to act rationally which means all players will tend to maximize their payoffs. The model identified the payoffs for each player as well as the stages of the game in order to reach equilibrium or recommended path. Two equilibriums were reached during the game. The first one was reached when the payer subsidizes the provider to the extent that it is

profitable and the second one, when the payer subsidizes the provider indirectly through the consumer to the extent that it is profitable.

System dynamics

The research developed by (Erdil & Emerson, Modeling the dynamics of Electronic Health Records adoption in the U.S healthcare system, 2008) was associated to the study of Electronic Health Records EHR adoption initiated with the identification of the barriers to EHR adoption in the form of a causal loop diagram. The causal loop diagram captured the cause and effect relationship in the form of feedback loops amongst the factors influencing the EHR adoption process. Following a system dynamics methodology (Erdil & Emerson, Simulation modeling of electronic health records adoption in the U.S healthcare system, 2009) and by using the structure of the causal loop diagram, a model to simulate the hospital's EHR adoption rate evolution over time was developed. Cost was identified as one of the main barriers to EHR adoption. The details of the model development and preliminary findings are presented in the dissertation (Erdil, Systems analysis of Electronic Health Record adoption in the U.S. healthcare system, 2009).

2.4 Comparative analysis (barriers, conceptual models and adoption determinants)

For the comparative analysis two technologies were considered: IOS/EDI and EHR.

The comparative analysis included the analysis of the main conceptual model elements (including barriers) among the selected technologies, 26 documents were reviewed as shown in Table 5. This analysis led to the identification of the main adoption determinants.

2.4.1 Non healthcare adoption process (IOS/EDI)

From the main set of non healthcare related adoption documents 13 documents associated with IOS/EDI adoption and implementations were reviewed. As noted by (Narayanan, Marucheck, & Handfield, 2009) there was no single model to explain the adoption and implementation of EDI from an organizational perspective, however, the main conceptual model is DOI and the adopting unit is the organization. The factors related to the adoption were classified into three groups (organizational factors, technology related factors and external or environmental factors) those groups can be identified in the work developed by (Grover, 1993) and (Nelson, 2003).

External factors, internal factors, organization related factors, expected benefits and inter organizational factors are among the factors affecting the adoption. The implementation and the expected outcomes are related to the intensity of the internal integration. The barriers to EDI adoption were explored by (Arunachalam, 1995).

2.4.2 Healthcare adoption process (Electronic Health Records)

As shown in Table 5 there are 13 documents related to the adoption of EHR. There are 2 documents related to conceptual models and 5 related to the identification of barriers to adoption.

Compared to IOS/EDI adoption, there are fewer adoption and implementation studies for EHR. Most of the studies are related to adoption, fewer documents are related to EHR implementation which gives an indication of the current EHR's adoption stage. Among the revised documents, the exploration of the barriers to EHR adoption is more predominant. This could be an explanation to the absence of a conceptual model for identification standards. The barriers can be considered in the absence of a conceptual model.

Table 5. Comparison

Category	Reference/ Author	Year	Type	Focus	Unit	Conceptual model	Approach
1	Grover [+]	1993	J	CIOS	O	Conceptual model	DOI & IS
	Vlosky et al	1994	R	Retail IO	O	None	None
	Nelson [+]	2003	D	IOS	O	Conceptual model	TOE
	Ramamurthy et al [+]	1995	J	Large firms	O	Conceptual model	DOI
	Iacovou et al [+]	1995	J	SMB	O	Conceptual model	general
	Arunachalan	1995	J	EDI users	O	Findings report	None
	McGowan and Madey b	1998	B	EDI	O	Conceptual model	DOI
	Niederman	1998	B	EDI	O	Literature review findings	DOI
	Palmer [+]	1998	B	EDI	O	Conceptual model	DOI
	McGowan and Madey a [+]	1998	J	EDI users	O	Conceptual model	DOI
	Iskandar et al	2001	J	Automotive	O	Conceptual model	general
	Kuan et al [+]	2001	J	SMB	O	Conceptual model	TOE
	Narayanan et al [+]	2009	J	EDI	O	Conceptual model	general
2	Miller and Sim	2004	J	EMR	E,O	Identification of barriers	None
	Ash and Bates	2005	J	EHR	O	Identification of barriers	None
	Middleton et al	2005	J	EHR	O	Recommendations	None
	Woodside	2007	J	EHR	O	None	None
	Chang et al [+]	2007	J	e-signature	O	Conceptual model	TOE
	Erdil	2008	C	EHR	O	Identification of barriers	SD-CLD
	Erdil a	2009	C	EHR	O	Simulation model	SD
	Erdil b	2009	D	EHR	O	Report on model findings	SD
	Hillestad et al	2005	J	HIT / EMR	O	None	None
	Shortliffe	2005	J	HIT	O	Identification of barriers	None
	Bower	2005	R	HIT/EHR	O	Conceptual model	DOI
	Fonkych and Taylor	2005	R	HIT	O	Identification of barriers	None
	Girosi et al	2005	R	HIT/EHR	O	None	None

[+] adoption determinant related document

2.4.3 Adoption determinants

In order to identify the adoption determinants, 9 documents were selected, eight of those documents were related to IOS/EDI and one was related to EHR adoption. The findings from each document related to the explored and empirically tested relationships between a given factor and adoption was analyzed; this way the main adoption determinants were identified. A detailed summary of the reviewed documents is presented in Appendix A. he summary of adoption determinants is presented in Table 6.

Table 6. Adoption determinants

TOE categories	Determinants	References
T	Compatibility	Grover (1993); Ramamurthy et al. (1995); Narayanan et al.(2009)
T	Complexity	Grover (1993)
T	Direct benefits	Iacovou et al. (1995); Kuan et al. (2001); Narayanan et al. (2009)
T	Indirect benefits	Iacovou et al. (1995); Ramamurthy et al. (1995); Narayanan et al. (2009)
T	Relative advantage	Grover (1993); McGowan and Madey (1998a)
O	Adequate resources	Chang et al. (2009)
O	Championship	Grover (1993)
O	Cost	Kuan et al. (2001)
O	Hospital size	Chang et al. (2009); McGowan and Madey (1998a); Palmer (1998);Narayanan et al.(2009)
O	Technical competence	Kuan et al. (2001)
O	Top management support	Grover (1993); Nelson (2003); Ramamurthy et al. (1995);McGowan and Madey (1998a)
E	Competitive pressure	Iacovou et al. (1995); Narayanan et al. (2009)
E	Customer influence	McGowan and Madey (1998a)
E	Government policy	Chang et al. (2009)
E	Imposition by partners	Iacovou et al. (1995)
E	Industry influence	Narayanan et al.(2009)
E	Vendor support	Chang et al. (2009)

Those determinants were grouped according to the TOE model categories. In the organizational category are: hospital size, top management support, adequate resources, championship, cost and technical competence. In the category of technology related factors are: compatibility, direct benefits, indirect benefits, relative advantage and complexity. In the category of environment related factors are: competitive pressure, vendor support, government policy, imposition by partners, customer influence and industry influence.

2.5 Summary of findings

This section presents a summary of the findings from the literature review related to technology adoption within healthcare and non healthcare domains.

2.5.1 Non healthcare vs. Healthcare (timing)

The adoption of technology to support basic manufacturing processes started at the end of the 1980s, and there is lag compared with the adoption of technology to support healthcare supply chain processes. Based on the date range of the documents in both groups, there is a difference of about 15 years, between the time EDI started to penetrate in the manufacturing setting and the initial time for EHR adoption initiation. According to the adoption phases defined by (Rogers E. M., 1983) the EDI adoption process includes both, adoption an implementation phases (Narayanan, Marucheck, & Handfield, 2009), however the EHR adoption is in an early stage. No implementation phase for EHR was found or documented in any of the reviewed documents.

2.5.2 Estimation of benefits

During early stages of the adoption process the benefits were estimated usually by comparison with similar industries. In the case of the healthcare supply chain a comparison with retail industry was usually referenced. An example of this fact is the work developed by RAND Corporation on Health Information Technology HIT. In the case of EDI the results of the meta analysis developed by (Narayanan, Marucheck, & Handfield, 2009) show inconclusive results regarding the benefits of EDI adoption.

2.5.3 Conceptual models (characterization)

As defined by the MOT approach, a conceptual model is used to explain a given adoption process. The explanation (characterization) of the adoption process is associated to the nature of the conceptual model (e.g DOI, TOE, TAM), the unit of adoption defined for the analysis (e.g. end user, organization), the phases (e.g. adoption, implementation) and the main adoption determinants or the barriers, in the absence of a conceptual model.

The non healthcare related adoption processes explored through the literature review can be characterized by the IOS/EDI adoption. The most relevant approach used to develop a conceptual model is the Diffusion of Innovations (DOI) approach. In the case of DOI the adopting unit can be defined as the organization. There are different stages of adoption as described by (Rogers, Diffusion of Innovations, 1983). The work developed by (Ramamurthy & Premkumar, 1995) and (Narayanan, Marucheck, & Handfield, 2009) in the case of EDI illustrate the different phases and its relationship between implementation and outcomes. Factors affecting adoption are different from implementation factors, the work of (McGowan & Madey,

Adoption and implementation of Electronic Data Interchange, 1998), (Nelson, 2003),(Iskandar, Kurokawa, & LeBlanc, 2001), and (Palmer, 1998) provide an indication of that fact even though some authors note that the difference is not significant when a short implementation time is considered.

The healthcare related adoption processes explored through the literature review can be characterized by EHR adoption. There is no dominant conceptual model among the healthcare related adoption processes explored in Section 2.2, however the TAM model was useful in explaining adoption from the end user perspective as in the case of (Daim, Chan, Amer, & Aldhaban, 2009) for Personal Health Records PHR, where an individual is making the decision or whether or not to adopt PHR. During the initial stage of an adoption process usually the barriers to adoption are explored as in the case of EDI (Arunachalam, 1995) and EHR (Ash & Bates, 2005), (Miller & Sim, 2004).

2.5.4 Modeling approach

As explained in Section 2.3.2, among the reviewed documents there is no dominant approach to model an adoption process. The relevant findings are related to techniques used in isolation. The more predominant technique was diffusion curves in particular for the non-healthcare related adoption processes. The use of game theory and system dynamics modeling was used to model EHR adoption.

2.6 Conclusion

The characterization of adoption process within the healthcare and non-healthcare domains was established, conceptual models were identified, as well as the adoption determinants and main

barriers. The findings presented a conceptualization of a given adoption process within healthcare and outside of the healthcare domain. This is a partial answer for the two research questions initially proposed. The need for the review of the data standards related literature in order to establish a comparison was evident; the comparison is developed in the next chapter.

3. Factors affecting identification standards adoption

The goal of this chapter is to answer the following research question as established in Chapter 1:

- *What is preventing healthcare supply chain members and healthcare providers in particular from adopting identification standards and its supporting technologies? What are the major barriers?*

This chapter reports on a literature review associated to data standards related literature in order to identify the main factors affecting the adoption process. Based on the findings from this literature review and the findings from the previous chapter, a comparison of the identification standards adoption process and the adoption of Electronic Data Interchange (EDI) and Electronic Health Records (EHR) was developed. A conceptual model to explain the factors affecting the identification standards adoption process was proposed. The link between the proposed conceptual model with subsequent modeling efforts is explained along with the implications of current findings.

3.1 Data standards related literature review

The literature review was initiated with the review of the documents available through the main trade journals (periodicals). The following periodicals were explored: Health Purchasing News (HPN), Modern Materials Handling (MMH), Healthcare Financial Management Association (HFMA) Journal and the Journal of the Healthcare Information and Management Systems Society (JHIMS). The ProQuest data base was used for the HFMA journal and for the MMH and HPN periodicals. The HFMA journal had full coverage since 1987, MMH had full coverage since 2004 and HPN had full coverage since 2001. The JHIMS was accessed from the

Healthcare Information and Management Systems Society (HIMSS) website, and the issues since 2005 were reviewed by topic, title and abstract. The basic terms for the search were *data standards* and *health care supply chain*; 93 articles matched the criteria. The initial set of documents was reviewed in order to establish if any of those documents had an explicit relationship to data standards adoption in total 27 articles were identified.

The 27 articles were fully reviewed and the review process led to the identification of 33 additional documents. A total 60 documents were identified and those documents were grouped in the following categories:

- Trade journals (27)
- Surveys and studies (8)
- Industry reports and white papers (13)
- GS1 related documents (6)
- Others (6)

The final set of documents was grouped by category in two parts A and B as shown in Tables 7 and 8 respectively. The classified documents were fully reviewed in order to establish the barriers to data standards adoption; the terms *conceptual model* and *mathematical modeling* were also included in the review. The results from the review by category are presented in the following section.

3.1.1 Findings by category

Trade journals

The industry perception of the identification standards adoption movement can be explained through the trade literature documentation. 27 documents were reviewed as shown in Table 7. The Department of Defense (DoD) pilot showed promising results for synchronizing data in healthcare, (Garvin, 2006) and the use of a Product Data Utility (PDU) as a centralized and standardized source of product related information. The concept of data synchronization was initially embraced by the DoD pilot. The results demonstrated the concept of a PDU for healthcare as a feasible one (Levine, 2007).

The efficiency of supply chain processes is clearly reduced due to the lack of a standardized or a unique numbering scheme. The FDA in 2004 established a rule requiring the labeling of drugs using the National Drug Code (NDC) number which was created to help reduce medication errors. However, medical devices were excluded from this barcode rule due to the lack of a unique numbering system for medical devices and supplies (Barlow, Sync or swim: Who should blink first and why?, 2007). The FDA's current authority only applies to device manufacturers; it cannot reach the provider side (Barlow, FDA Negotiates through device data standards stalemate, 2010). The FDA also presents the option of multiple standards and not to endorse a particular one. They believe the industry would benefit more with the presence of multiple standards since it could leave the door open for the development of options that could address identification issues that neither GS1 nor HIBCC can adequately address (e.g. ISBT 128 standard for tissues).

Table 7. Identification standards literature review Part A

Category	Author	Date	Journal or Document Title	Topic
Trade Literature	Garvin*	may-06	Healthcare Purchasing News	Data synchronization
	Barlow	abr-07	Healthcare Purchasing News	Sync or swim+
	Levine	abr-07	Healthcare Purchasing News	DoD Pilot results
	Barlow f	jun-08	Healthcare Purchasing News	Data Standards precautions
	Barlow d*	abr-09	Healthcare Purchasing News	Stimulus package
	Barlow e	may-09	Healthcare Purchasing News	Premier
	Perrin	sep-09	Healthcare Purchasing News	Supply chain standards
	Barlow*	dic-09	Healthcare Purchasing News	Year end
	Barlow c	feb-10	Healthcare Purchasing News	FDA viewpoint
	Barlow b*	feb-10	Healthcare Purchasing News	VHA viewpoint - Alliance
	Barlow a*	feb-10	Healthcare Purchasing News	Deadlines
	Langabeer	2005	JHIMS	Supply Chain IT
	Thompson et al.	2007	JHIMS	Benefits EHR+
	Murphy*	2008	JHIMS	HIT adoption
	Blachowicz et al.	2008	JHIMS	Future EHR ROI
	Krohn	2009	JHIMS	Interoperability
	Burke et al.	2009	JHIMS	Best of Breed strategies
	Edwards et al.	2010	JHIMS	Barriers related to HIE and EHR
	Berling and Geppi	1989	Healthcare Financial Management	Early supply chain concepts
	Moynihan	1997	Healthcare Financial Management	EHCR related - EDI adoption+
	Brennan	1998	Healthcare Financial Management	EHCR related+
	Brody	2007	Healthcare Financial Management	Data synchronization
	Belkoski*	2008	Healthcare Financial Management	Retail model+
	Kowalsky	2009	Healthcare Financial Management	Strategic approach
	Burke	2008	Materials Management in Healthcare	DoD Pilot lessons learned
	Burke	2008	Materials Management in Healthcare	DoD Pilot lessons learned
	De John	2008	Materials Management in Healthcare	Standards in motion+

* barrier related document

+ benefits related document

Table 8. Identification standards literature review Part B

Category	Author	Date	Journal or Document Title	Topic
Surveys and Studies	EHCR	1996	Improving the efficiency of the healthacare supply chain	Supply Chain Strategies+
	AHA Survey*	2005	Forward Momentum	HIT = EHR most of the time
	AHA Report	2006	Adopting Technological Innovations in Hospitals	focus HIT
	AHA Survey*	2007	Continued Progress	focus HIT in general
	HFMA Survey	2005	HFMA 2005 healthcare supply chain benchmarking survey	Opportunities+
	HFMA Survey	2008	HFMA 2008 healthcare supply chain survey	Opportunities+
	CHIL Survey*	2009	The State of Healthcare Logistics	Barriers to IdS adoption
	HIMSS report*	2010	E-procurement for supply chain management	EDI adoption
Industry Reports	Garg et al	1999	17 Billion Reasons to Say Thanks	Cost and benefits UPC+
	HIMSS report*	2003	Guide for the Use of BC Technology in Healthcare	Focus on drug administration
	McKesson white paper	2004	Healthcare supply chain management and the internet	eCommerce focus+
	ATKS report	2004	Connect the dots	EPC and GDS focus+
	Hefflin (ECRI)*	2005	Automatic Identification of Medicel Devices	UDI challenges
	ERG*	2006	Unique identification for medical devices	UDI challenges+
	Rosenfeld	2006	Data Synchronization in Healthcare: A Solvable Problem	GDSN Healthcare roadmap+
	Accenture	2006	Synchronization	GDSN benefits (retail)+
	Shemm et al	2007	Global Data Synchronization	GDSN trends+
	MIT CTL report	2006	Transforming the Healthcare Supply Chain	HCSC problems+
	The academy study	2008	SCM Practices of the Largest Health Systems	Best practices+
	Lawson white paper	2008	Getting Started with Standards Based Operating Procedures	Implementation road map+
	Simpson and Kleinberg	2009	Implementation Guide to Bar Coding ain Healthcare	Pharmaceutical adm. Related
GS1 related	Bix et al	2007	Global Data Standards in the Healthcare Supply Chain	Costs and benefits+
	DoD Pilot Report	2007	Results from DoD HealthcareGDSN Pilot Phase IIA	Lessons learned GDSN pilot+
	GS1 and HCSC	2009	GS1 Standards in the Healthcare Supply Chain	Definitions+
	Seton	2009	A GS1 Healthcare US Success Story	Perfect order definition
	GS1 System of standards	2010	The Value and Benefits of the GS1 System of Standards	Definitions
	ChES HIGPA Survey*	2009	Putting the Pieces Together	IT solution provider focus

* barrier related document

+ benefits related document

Some Integrated Delivery Networks (IDNs) have called for the government to support the use of GS1 standards as they support and promote the use of Electronic Medical Records (EMR) (Barlow, Alliance subgroup throws down device data standards gauntlet, 2010). According to the authors there is no sense if a hospital has an EMR and still has to key in the product numbers due to the lack of standards and automation at the point of use.

The Efficient Healthcare Consumer Response (EHCR) initiative (CSC, 1996) was referenced as the main starting point addressing the issues such as: the lack of unique identifiers for products and locations, the lack of EDI capabilities at the healthcare provider level and the low penetration of point of use barcode enabled technology (Moynihan, 1997). However, just until 2007 standards movement started to take shape. This movement was followed by the positive results from the Department of Defense (DoD) pilot (Burke, Hospitals lessons in data synchronization, 2008), (Burke, Progressive Pilots, 2008) on testing the Product Data Utility (PDU) as a feasible concept for the healthcare industry.

Industry groups are collaborating to promote data standards adoption (Barlow, Alliance subgroup throws down device data standards gauntlet, 2010). The FDA is also working on the draft of a UDI regulation for medical devices and supplies. Technology adoption plays an important role on data standards adoption as explained by (Langabeer, 2005). This is a key issue to be addresses in this research, the relationship between technology adoption and adoption of standards at the healthcare provider level. It is assumed that the underlying technology should be installed and running for identification standards adoption and use.

Surveys and studies

Within the surveys and studies category, 8 relevant documents were identified. The initial study (CSC, 1996) identified three main strategies and four main enablers for healthcare supply chain improvement. Among the strategies were efficient product movement, the efficient order management and the efficient information sharing. The four enablers were categorized in strategic and tactical. At the strategic level: partnerships and alliances, and change management. At the tactical level: information technologies and activity based costing. Within the information technologies enablers, the critical technologies identified were: unique identifiers, bar code labeling and EDI. The main elements on the third strategy include solution sets directly related to the implementation and use of identification standards and its supporting technologies.

The surveys developed by the American Hospital Association (AHA) (AHA, 2006),(AHA, 2007), (AHA, 2005) were related to the adoption of HIT for clinical and non clinical purposes by US hospitals. From these documents the current status of one of the most important clinical applications, the EHR, was inferred. The penetration rate for EHR is about 32%. The barriers to adoption were also explicitly mentioned but those barriers were usually associated with the adoption of HIT in the context of Electronic Health Records. The main barriers were: the initial costs, ongoing costs, interoperability with current systems, acceptance by clinical staff, availability of trained IT staff and the inability of technology to meet the process requirements.

The survey developed by (Nachtmann & Pohl, The State of Healthcare Logistics: Cost and Quality, 2009) referenced the technological component as one of the main barriers to data standards adoption. Among the other barriers were the lack of resources, supply chain partners,

universal acceptance, lack of knowledge, system diversity, management buy-in, data issues, organization size, government, low priority and cultural resistance.

The surveys showed that the data standards movement initiated in 2007 had an impact on industry perceptions. The HFMA surveys of 2005 and 2008 (HFMA, 2005), (HFMA, 2008) provided an indication of that fact. The HFMA survey of 2005 did not show data standardization as an explicit opportunity for improvement, but it appeared in the 2008 survey as a significant one. The survey developed by (Nachtmann & Pohl, The State of Healthcare Logistics: Cost and Quality, 2009) also indicated that data standards are a major issue, labeling it as one of the main challenges to achieve supply chain excellence. Some confusion still exists regarding the definition of data standards, as pointed out by (Kohn, Corrigan, & Donaldson, 2000). The data standards concept is too broad. It could mean: standardization within the hospital, process standardization or the use of standard identifiers for products and locations. A specific reference to the definition of data standards in the context of the explored surveys was not found.

Industry reports

Within the industry reports category, 13 relevant documents were identified. The report by (Garg, Jones, & Sheedy, 1999) described the methodology followed in order to establish the gains of the Universal Product Code (UPC) adoption by the grocery industry; the gains were estimated to be approximately 17 billion dollars. Hard savings and soft savings were initially estimated and the report showed how most of the gains can be attributed to hard savings, however, the soft savings are still to be realized.

The report by (HIMSS, 2003) referred to the use of barcode technology in healthcare but is directly related to drug administration. This report highlighted the importance of the National Drug Code (NDC) as an identifier for most of pharmaceutical products but calls the attention of most of the healthcare supply chain players on its proper use. Following the report by HIMSS, two reports were published. The first one, developed by (McKesson, 2004) related to electronic commerce and the second one developed by ATKS (ATKS, 2004), related to Electronic Product Code (EPC) adoption. Both reports highlighted the importance of standards for electronic transactions and identified the critical elements required for electronic commerce in healthcare. The Unique Device Identification (UDI) initiative was discussed by (ERG, 2006) and (Hefflin, 2005). Among the main barriers to UDI implementation were the lack of a unique identifier for medical devices and supplies and the low technology (auto identification and data capture) penetration at the healthcare provider level in particular at the point of use.

The report by Accenture (Accenture, 2006) described the benefits of data synchronization in the retail context and presented an estimation of benefits of its adoption within healthcare. The report by (Shemm, Legner, & Otto, 2007) discussed the Global Data Synchronization Network (GDSN) from a global perspective. The report by (Rosenfeld & Stelzer, 2006) described the synchronization concept in healthcare and compared it with what has been done in retail. According to the authors, the gains from data synchronization could be significant, if healthcare industry moves in that direction. The report also presented some tools to estimate the benefits of data synchronization in healthcare.

The (CTL, 2006) report described the main problems identified within the healthcare supply chain, in fact, some of the identified problems were: cost growth, lack of a big player at the end

of the chain, process inefficiency and lack of integration of the last echelon; from the receiving dock to the doctor. The lack of a unique identifier for healthcare products is also highlighted as one on the major challenges. The study developed by (The Academy and Broadlane, 2008) revealed a set of practices common among the best performer hospitals. Among the best practices were: leadership and corporate office presence for supply chain related issues, existence of system wide policies and physician engagement. The report by (Lawson, 2008) described a roadmap for data standards implementation along with a check list for information technology and system readiness. The book by (Simpson & Kleinberg, 2009) was related to the implementation of barcode technology in clinical and supply chain applications. This book made explicit reference to the need of a standard for product identification and revealed the implications of its absence for all healthcare supply chain players.

The retail industry was used as a reference point to estimate data synchronization benefits. The UDI initiative was presented as a possible solution to fix the problem of the lack of unique identifiers for medical devices and supplies. The main problems related to healthcare supply chain are associated to the lack of a unique identifier as a main source of process inefficiencies. In this regard, having a unique identifier for products and locations would help to increase supply chain related processes efficiency and also facilitate information exchange and synchronization among healthcare supply chain members.

GS1 documentation

Within the GS1 related documentation category, 6 documents were identified. The effort on data standardization within the medical surgical supply chain was initiated by the Department of Defense (DoD, 2007). The conceptualization of the Universal Product Number (UPN) as a

unique identifier for medical surgical supplies (including devices) and the development of the PDU concept as a unique repository for product related information were among the main contributions of the initial phases of the DoD pilot. This pilot in recent versions involved major healthcare supply chain players and it was proving the Global Data Synchronization Network (GDSN) as a feasible concept for the healthcare industry. The study developed by (Bix, Clarke, Lockhart, Twede, & Spink, 2007) was an extensive study on the costs and benefits of standards adoption. It gave basic definitions regarding the hospital supply chain and presented a compilation of previous studies dealing with cost benefit estimation of automation within the healthcare supply chain.

Basic definitions about standards and health care supply chain are given by (GS1, 2009), (GS1, 2010). The main source for GS1 data standards related information is the official GS1 Healthcare US website. Specific deadlines for product and location identification standards adoption have been established by the industry. The deadline for location identifiers adoption was December 31st 2010 and the deadline for product identifiers is December 31st 2012. Currently the healthcare industry is moving towards the readiness assessment of the different healthcare supply chain players, but adoption remains low. The readiness assessment is voluntary and GS1 healthcare US is providing tools for healthcare supply chain members who would like to assess their current adoption level. The assessment of technology solution providers (ChEs HIGPA GS1, 2009) revealed that most of the technology solution providers could at least store the identifiers; however, the transaction capabilities are still an issue to be resolved.

The documents reviewed in this section included documents related to key definitions, however, case studies were not considered. The review of those cases is out of scope for this research but its importance is acknowledged. The GS1 system of standards is currently the standard being promoted, but it could be any standard, for analysis purposes, as long as it is unique. The focus of this research is not GS1 standards; it is the concept of product and location identifiers standards adoption along with the required technology to make use of the standards. It is assumed that technology plays a key role in identification standards adoption.

Others

Within this category a brief exploration of the identification standards adoption concept among the pharmaceutical supply chain was developed; 6 documents were identified. An earlier document dated 1996 (Bedard, 1996) presented the fact that even though the barcode technology was present, it was not widely deployed within healthcare industry, this problem is still persistent. The GS1 documentation is related to the traceability and electronic pedigree initiatives within the pharmaceutical supply chain (GS1 US, 2010). The pharmaceutical supply chain related documentation is a reference point for Bedside Point of Care (BPOC) systems and Barcode Medication Administration (BCMA) adoption. The report developed by (Grotting, Yang, Kelly, Brown, & Trohimovich, 2002), presented the benefits and barriers of BPOC systems in the context of patient safety through the use of case studies. The workarounds to BCMA adoption are explained by (Koppel, Wetterneck, Telles, & Karsh, 2008) and among the possible causes is the lack of medications with a barcode. The adoption of BCMA from the end user perspective is explained by (Patterson, Chapman, Render, & Rogers, 2006), the authors found that when workaround strategies were used in order to increase efficiency, new potential

paths for adverse drug events were generated. The end user perspective was studied by (Tian, Duffy, Birk, Abel, & Hultgren, 2009), in this work the authors use the TAM model to explain BCMA adoption within hospitals. The penetration of BCMA among hospitals remains low; it is reported as 10% (Cummings, Ratko, & Matuszewski, 2005).

3.1.2 Findings by topic

This section summarizes the findings related to the benefits and barriers, being the most common topics referenced in the literature. No conceptual model related document was found. Other topics such as the healthcare provider perspective and the identification standards definition will be referenced through the development of the conceptual model.

Benefits of data standards adoption

From the set of identified documents, 22 documents were related to data standards adoption benefits. The broad benefits of adopting identification standards were related to the increase of supply chain processes efficiencies and the increase of patient safety. Among these benefits were: efficient traceability (Rosenfeld & Stelzer, 2006); improved ordering, invoicing and receiving processes (CSC, 1996); reduced data cleansing efforts (Accenture, 2006); ability to better monitor product recalls; track expiration dates and product authentication (Hefflin, 2005) and reduction on medication administration errors (Kohn, Corrigan, & Donaldson, 2000). Most of the estimations were based on industry predictions and by developing a comparison with the retail industry. As explained in Chapter 2, when an adoption process is in its early stage, the benefits are estimated by comparison with other industries and case specific findings (pilot studies).

In the case of EDI adoption, the adoption and implementation phases were developed (Narayanan, Marucheck, & Handfield, 2009), but most of the implementation studies showed inconclusive results regarding the benefits achieved from its adoption. The adoption of EHR is in a similar stage as data standards adoption; benefits have been estimated but currently not realized. In the case of EHR, (Thompson, Osheroff, Classen, & Sittig, 2007) points out that there is no widely standardized method to estimate or measure EHR adoption benefits. The authors provided a summary of an analysis conducted on the topic with more than 100 hospitals. The different methods used estimate the benefits are vendor supplied data, comprehensive studies, logical modeling, focused studies and site visits; the first option is the most common one. The authors proposed the development of a national database where hospitals can self-report best practices, lessons learned as well and costs and benefits. This will take time to develop but it could ensure the compilation of the information for further use. A similar structure could be developed for identification standards adoption assessment.

Barriers and challenges

From the set of initial documents, 15 documents were directly related to the barriers or challenges of data standards adoption. Those documents were fully reviewed and an initial list of barriers was developed, 34 items were identified. The barriers are grouped in 9 categories as shown in Table 9. No explicit document dealing with the barriers of data standards adoption was found.

3.2 Comparison EDI/EHR (conceptual models and barriers)

As explained in Section 3.1, there are no documents related to any conceptual model developed to describe the identification standards adoption process. In the absence of a conceptual model for identification standards adoption, it was not possible to develop a comparison between the conceptual models found in Chapter 2 which describe the adoption of EDI and EHR and a conceptual mode for identification standards. In this case a general analysis regarding the conceptual models was developed along with a comparison based on the identified barriers for the 3 adoption processes under analysis.

Table 9. Identification standards barriers

	Barrier category	# of items	Reference documents
1	High cost	7	(Garvin 2006) (Barlow d 2009) (Barlow 2009) (Barlow a 2010) (Murphy 2008) (AHA Survey 2005) (AHA Survey 2007) (CHIL Survey 2009) (HIMSS report 2010)
2	Organizational capabilities	7	(Murphy 2008) (AHA Survey 2005) (AHA Survey 2007) (CHIL Survey 2009) (HIMSS report 2010)
3	Lack of a standard	6	(Barlow d 2009) (Barlow a 2010) (Belkoski 2008) (CHIL Survey 2009) (HIMSS report 2010) (HIMSS report 2003) (Hefflin 2005)
4	Technology	4	(AHA Survey 2005) (AHA Survey 2007) (CHIL Survey 2009) (ChES HIGPA Survey 2009)
5	Lack of gov. intervention	3	(Barlow b 2009) (Barlow a 2010) (CHIL Survey 2009)
6	Lack of ROI	2	(Barlow b 2009) (Murphy 2008)
7	Interoperability issues	2	(Barlow d 2009) (Barlow b 2009) (AHA Survey 2005) (AHA Survey 2007) (CHIL Survey 2009)
8	Supplier reluctance	2	(CHIL Survey 2009) (HIMSS report 2010) (ERG 2006)
9	Lack of solution providers support	1	(Barlow b 2009) (Barlow a 2010)

3.2.1 General comments

The EDI adoption process was characterized by the use of DOI theory. This adoption process has been mostly studied from the organizational perspective. The adoption and implementation phases were present on most of the studies. The initial EDI adoption related studies were conducted in the late eighties.

The review of the EHR adoption process did not show any relevant conceptual model. However it included the end user (clinician or nurse) perspective when analyzing the adoption problem.

The EHR adoption process is in the initial stage, most of the adoption studies are dated beginning of 2004.

The identification standards adoption process is in a similar stage as the adoption of EHR, however, according to the literature the identification standards adoption process started in 2008. The timeline for EDI, EHR and Identification Standards (IdS) adoption is illustrated in Figure 5.

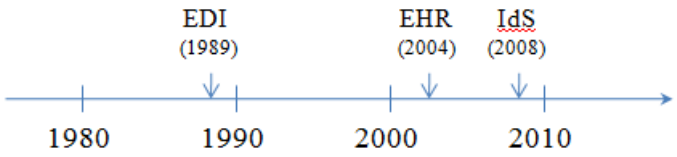

Figure 5. Innovations introduction timeline

3.2.2 Barriers

As established in Section 2.4, the EDI barriers are summarized in the work of (Arunachalam, 1995), among the barriers to EDI adoption are the interoperability related issues, the lack of a

standard, technology issues and the lack of ROI. The EHR barriers are cited by (Miller & Sim, 2004),(Ash & Bates, 2005) and (Erdil & Emerson, Modeling the dynamics of Electronic Health Records adoption in the U.S healthcare system, 2008), among the main barriers to EHR adoption are the high costs, technology issues and the lack of ROI. There were common facts that appear along the three adoption processes. Among those were the following: organizational capabilities, lack of Return on Investment (ROI) and technology related issues. There were some unique facts related only to identification standards adoption: the lack of government intervention and solution provider support. The results of the comparison are summarized in Figure 6.

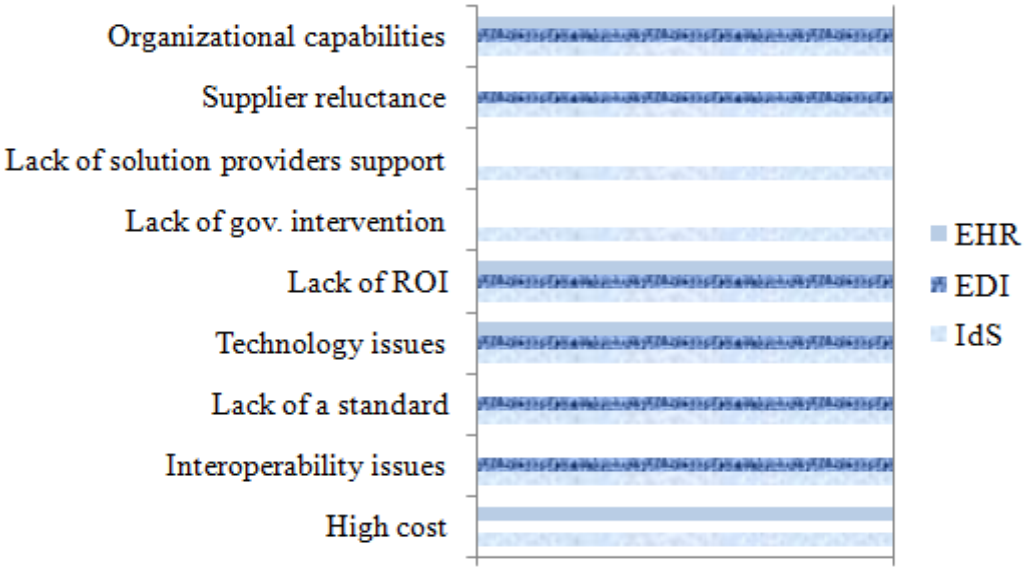

Figure 6. Barriers (comparison)

The review showed that in contrast to the EDI and EHR adoption processes described in Chapter 2, there are no documents related to a conceptual model or mathematical modeling approach for the identification standards adoption process, or at least those documents were not found.

Through the literature review the need of a perspective to analyze the identification standards adoption problem and the need for an operational definition for the concept of data standards were identified. These two issues are addressed in Section 3.3.1. A conceptual model for data standards adoption is proposed in Section 3.3.

3.3 Conceptual model for identification standards adoption

As mentioned in Section 3.2 the need for a perspective and an operational definition was identified in order to proceed with the analysis of the identification standards process and the development of a conceptual model. This need was also supported by the findings in Chapter 2 that indicate that such definitions are a pre requisite for a conceptual model definition.

The justification of the healthcare provider perspective and the operational definition for data standards in the context of this research is presented in the following paragraphs.

3.3.1 Basic definitions

Healthcare Provider Perspective

The chicken and egg problem of technology adoption described by many authors such a (Simpson & Kleinberg, 2009) and (Barlow, Alliance subgroup throws down device data standards gauntlet, 2010) can be analyzed if a perspective is considered. A specific view point is required to analyze the problem and would be useful when solutions to the problem are proposed.

For identification standards adoption, the healthcare provider perspective was defined as the main element to drive the adoption process; it is assumed that there is a pull effect from the

healthcare provider to the manufacturer which can speed up adoption. The healthcare provider perspective is supported by (Barlow, Crafting the supply chain stimulus package, 2009) and (Burke, Hospitals lessons in data synchronization, 2008). As pointed out in (HIMSS, 2003) some of the most significant implications of barcode labeling at the point of care and throughout the supply chain are: the need for industry standards to define the format of the label; the need for manufacturers and distributors to support barcode labels at the unit required for transactional purposes; and healthcare providers to implement processes to utilize the barcode products and systems to improve patient care.

Technology is a key issue in data standards adoption and implementation. Given the fact that hospitals devote more resources to technologies that support patient care than to the supply chain (Kowalski, 2009), the problem is even more relevant. Related to supply chain technology two types of investments are clearly defined: information systems such as a specialized supply chain module or an ERP supply chain module and also automation technology which could include point of use systems that track inventory on hand, storage carousels, and warehouse management systems. According to (Langabeer, 2005), there is a significant gap between healthcare and the evolution of information systems to support supply chain management processes in other industries such as retail or manufacturing and healthcare industry.

Operational definition (identification standards)

In the context of this research the terms *data standards* and *identification standards* are equivalent. As explained by (Krohn, 2009), the data standards definition is too broad, so a definition was needed as an initial step in the analysis of the adoption process. An operational definition such as the one given by (Bower, The Diffusion and Value of Healthcare Information

Technology, 2005) in the case of EHR and by (Narayanan, Marucheck, & Handfield, 2009) in the case of EDI is required. For example, (Bower, The Diffusion and Value of Healthcare Information Technology, 2005) in his work defined that a healthcare provider had EHR if it has purchased a set of applications (i.e Clinical decision support systems, Computarized patient records and Clinical data repository), within a given period of time.

For identification standards the operational definition includes a process-technology based approach. Three types of processes are defined. Processes type I are external supply chain processes associated with external supply chain partners. Processes type II are internal supply chain processes. Processes type III are supply chain processes related to the final product delivery which includes the patient. The adoption within processes type I is associated to the presence of the required systems (supporting technologies) to operate with the standards, for example EDI or a MMIS. For processes type II a level of automation is required this includes supply chain solutions with barcode enabled capabilities. For processes type III the required technology is automation at the point of use.

The concept of perfect order as defined by (GS1, 2009) was used as an initial reference point to define identification standards adoption within the conceptual model scope. The concept of the perfect order has been around since 2008 and it has its roots in the work of the manufacturer BD within the scope of the DoD pilot. A perfect order is defined as a purchase order processed electronically from order to payment without human intervention, delivered to the right location, on time, undamaged, at the right price, in the desired quantity on the first attempt. According to this definition a healthcare provider (hospital) with the capability of sending and receiving an

EDI order which includes product and location identifiers would be recognized as an adopter of identification standards.

3.3.2 Factors affecting the identification standards adoption process

The proposed conceptual model for identification standards was based on the findings from the literature review developed in Chapter 2 and the findings of the literature review on data standards conducted in this chapter. It was assumed that factors which have been found relevant to other technological innovations (adoption determinants) could help to explain the adoption process under study.

A conceptual model for identification standards adoption needs to consider the factors that affect the adoption and use of the innovation (data standards). The extensive literature review developed in Chapter 2 suggested that the Technology Organization and Environment (TOE) conceptual model (Tornatzky & Fleisher, 1990) is appropriate to define and study the factors that influence identification standards adoption.

This conceptual model defines three aspects of an organization that influence the adoption of a given innovation. The technological context describes the characteristics of the innovation to be adopted in relationship with the readiness level of the organization. The organizational context is related to the characteristics of the organization such as size and top management involvement. The environmental context is related to the external factors that influence adoption, such as government and industry players. The TOE model is consistent with the innovation diffusion theory (Rogers E. M., 1983) which defines technological characteristics and both, the internal and external characteristics of the organization as drivers for technology adoption and diffusion.

In order to develop the conceptual model, the barriers for identification standards were compared with the list of adoption determinants established in Chapter 2. An association between the identification standards adoption barriers shown in Table 6 and the adoption determinants listed in Table 9 was developed. After the analysis, 8 of the adoption determinants were considered along with new elements related only to identification standards adoption (identified through the literature review). The specific elements related to identification standards adoption were associated to the readiness level of the organization (healthcare provider) process and technology wise; and the readiness level of the technology solution provider. The final set of eleven factors that are associated to identification standards adoption was grouped by TOE category as shown in Table 10.

The proposed conceptual model is illustrated in Figure 7. Each factor within the model is related to the healthcare provider adoption decision. The factors are grouped by TOE category. The technology related factors are relative advantage, complexity, compatibility and the organizational readiness factor in terms of the technological capabilities. These factors are directly associated with the characteristics of the technology (innovation) under study and the preparedness of the organization related to its infrastructure to support the adoption. The relative advantage represents in aggregate terms the gain from its adoption. The environment related factors are industry pressure, government intervention, vendor support and the technology solution provider readiness factor in terms of its ability to support the technology to be adopted by the healthcare provider. These factors are outside of the control of the healthcare provider. The organization related factors are size, top management support, and organizational readiness factor. These factors are directly related to key characteristics of the organization (e.g size) and also to basic elements of the project and team required to lead the adoption process.

Table 10. Proposed adoption determinants

	TOE category	Factors
1	T	Relative advantage
2	T	Compatibility
3	T	Complexity
4	*T*	*Organization readiness (technology based)*
5	O	Top management support
6	O	Hospital size
7	*O*	*Organization readiness (process based)*
8	E	Industry influence
9	E	Vendor support
10	E	Government policy
11	*E*	*IT Vendor readiness*

3.3.3 Conceptual model validation

The conceptual model was validated with the use of industry expert's interviews. Two experts from a medium size medical center; the information technology IT Vice President and the supply chain manager were interviewed in order to validate the factors proposed by the conceptual model. The categorization of factors using the TOE model structure was understood and it was found relevant. Regarding the organization related factors, the top management support and organizational readiness factors were highlighted as important ones. The organization size was not perceived as a major factor affecting adoption. The organizational readiness was directly related to the technological infrastructure and the maturity level of the solution (i.e. data standards). The return on investment from the adoption of data standards is not seen as an immediate fact but a result of the collaboration among supply chain partners. According to the experts that is one of the reasons why healthcare providers have to start pulling in order to drive the adoption process.

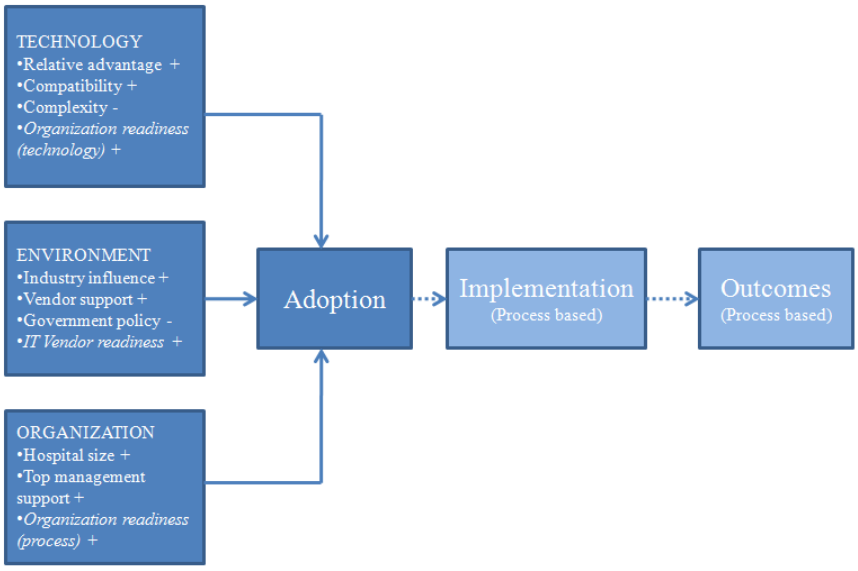

Figure 7. Proposed conceptual model

For example healthcare providers would benefit from the use of barcode labeled products if manufacturers are willing to do the task of labeling them; but healthcare providers have to start implementing barcode enabled processes. The solution's compatibility and complexity are also seen as drivers of adoption. In this case the data standards solution should be compatible with existing systems and the complexity of its implementation should be low. There are external forces that could drive adoption and certainly the IT vendor readiness is one of them as well as the pressure from the government and other industry partners.

3.4 Mathematical modeling approach for identification standards adoption

The identification standards literature reviewed in this chapter did not reveal any mathematical modeling approach. The use of diffusion theory and system dynamics modeling is proposed to develop an approach to model the identification standards adoption process. The development of

the model includes the transition from the conceptual modeling phase to the mathematical modeling of the adoption process.

The factors identified through the conceptual model are used in the causal loop diagram and simulation model development. The initial mathematical model is proposed as an extension of the Bass diffusion model and will be used to simulate the behavior of the hospital population over time and to observe the impact of the external and internal diffusion coefficients in the adoption rate. The simulation model will allow for the analysis and design of policies to move the adoption process forward. The development of the modeling approach for identification standards is presented in Chapter 4.

3.5 Conclusions

This chapter presented the identification standards adoption process from an academic perspective using the elements provided by the literature review on management of technology MOT and current findings from data standards adoption literature. The exploration and identification of the factors affecting the identification standards adoption process is the initial step toward understanding the adoption of data standards.

The conceptual model proposed in this paper was developed based on an extensive literature review related to the identification standards adoption literature as well as technology adoption literature. The conceptual model for identification standards adoption is proposed as a way to answer the research question defined at the beginning of this chapter and to fulfill the goal of Phase I.

4. Modeling Approach

The goal of this chapter is to answer the following research question as established in Chapter 1:

- *How could existing diffusion models be extended or modified to model the identification standards adoption process?*

A systems dynamics modeling approach is used to model this process. The model is based on the diffusion of innovations theory; the main factors identified on Chapter 3 are used to develop the Causal Loop Diagram (CLD). For the model formulation it is assumed that classic diffusion models can be extended to model identification standards adoption. The developed model will facilitate the understanding of the system (healthcare supply chain) behavior and allow for the design and test of policies to move the system forward.

The use of technology diffusion models, such as the Bass Diffusion Model (BDM), for the model formulation presents some limitations which are explained and a way to overcome those limitations is presented. One of the most important limitations is the need of data on past adoptions which is lacking in the case of identification standards. Among the solutions to overcome this issue is the staged formulation proposed in this chapter. Two model stages are proposed. The Stage 1 or initial model formulation stays close to the basic BDM and is used to simulate the behavior of the hospital population over time and to observe the impact of the external and internal diffusion coefficients in the adoption rate of identification standards' supporting technologies. The implementation of the formulation for stage 1, the estimation of the base run, and the model validation are explained in this chapter.

The Stage 2 of the model formulation includes the process followed to formulate the model based on the CLD taking into consideration the proposed identification standards definition and the lessons learned from Stage 1. The model is based on system dynamics and diffusion theory and provides a model to understand and test interventions to promote adoption of Identification Standards (IdS). The implementation of the formulation for Stage 2, the estimation of the base run as well as model validation is explained in the next chapter. The model development and implementation fulfills the goal established for phase II of the research methodology as presented in Chapter 1.

4.1 Literature review

The literature review presented in this section compiled information from three different sources. The first one, the literature review developed in Chapter 2 which was related to technology adoption within the healthcare and non-healthcare domains. Among the identified documents an exploration of mathematical approaches to model adoption was performed; within the 41 documents identified in the literature review, 4 documents described a mathematical approach to technology adoption and diffusion. The main topics identified were the following: diffusion curves, system dynamics, game theory and agent based modeling (See Section 2.3.2).

The second source, the literature review developed in Chapter 3, which was related to the identification standards literature, concluded that no modeling approach was found within the identification standards literature and that there was an absence of a clear definition of the identification standards concept. These two particular issues are addressed in this chapter. The proposed modeling approach for identification standards adoption and the proposed definition are developed in order to explain the identification standards adoption process.

The third source, a specific search on System Dynamics SD methodology was extended through the development of Chapters 4 and 5. The SD methodology and technology diffusion perspective were also explored in order to understand and justify the methodology. Some of the references are: the diffusion modeling book by (Mahajan, Muller, & Wind, New Product Diffusion Models, 2000) provided useful information associated with the estimation of model parameters. The papers on sensitivity analysis (Ford & Flynn, 2005), (Hekimoglu & Barlas, 2010) describe how sensitivity analysis of system dynamics models can be performed in order to identify main parameters and key issues. The design of interventions was documented by the work of (Fisher, Norvell, Sonka, & Nelson, 2000), (Daim, Rueda, Martin, & Gerdsri, 2006) and (Cui, Zhao, & Ravichandran, 2011).

4.2 Modeling approach for identification standards adoption

As implied by the System Dynamics (SD) methodology described by (Coyle, 1983), the purpose of a model is to understand the structure of the system and to provide an insights into the possible solutions to the existing problems. The system dynamics methodology is suitable in the study of complex systems, where the interaction among factors is the possible cause of the problematic situation. As explained by (Sterman, 2000) it allows researchers to model the system at an aggregated level as shown in Figure 8. This level of aggregation facilitates the understanding and formal analysis of the system under study (Borshchev & Filippov, 2004).

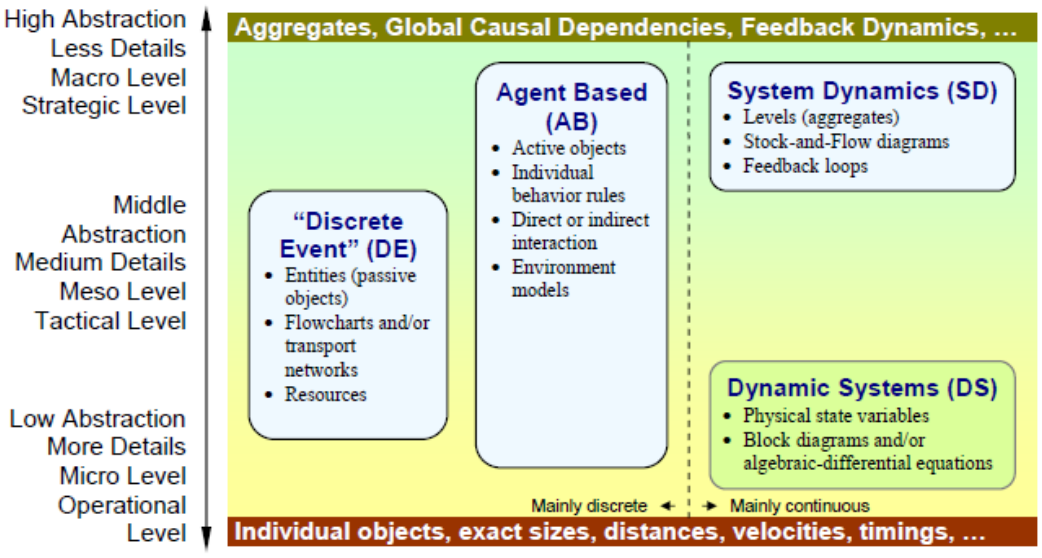

Figure 8. Modeling levels of aggregation (adapted from Borshcev and Filippov, 2004)

The system dynamics methodology is followed to model the identification standards adoption process using the steps described below:

1. Definition of the real world symptoms to be understood and improved
2. System description by the use of a causal loop diagram
3. Model formulation and simulation model development (structure)
4. Model implementation and validation
5. Simulation experiments
6. Analysis and results

The steps are followed sequentially but once the model is formulated and Step 6 is reached the process goes back to Step 3 until a satisfactory level of analysis is achieved. The complete sequence of the research methodology for Phase II is illustrated in Figure 3.

4.2.1 Causal loop diagram

The causal loop diagram is a formalization of the findings regarding the possible causes for the slow adoption process and it contributes to the identification of the feedback structure of the system under analysis. A causal loop diagram consists of factors connected by arrows denoting the causal influences amongst them. The causal loop diagram is another representation of the factors affecting the adoption process, and it is one of the initial steps in the system dynamics SD methodology. The causal loop diagram was developed to identify the relationships among the different factors affecting the healthcare provider adoption, and it is a bridge between the conceptual model proposed in Chapter 3 and the mathematical model proposed to simulate the identification standards adoption rate.

4.2.2 Model formulation

The Bass diffusion model is defined as the basic formulation for the model. The model formulation follows a two stage process. Stage 1, or initial approach, in which the Bass Diffusion Model (BDM) is used to mathematically describe the adoption process. Stage 2 is based on the causal loop diagram (CLD) and includes most of the empirical relationships within the factors defined in the CLD.

4.2.3 Model implementation and validation

The model formulation was implemented in Vensim modeling software (version PLE Plus). This tool was used in this research to develop the causal loop diagram and to implement the model formulation. The Vensim model or simulation model facilitated the exploration of the impact of the different factors on the adoption rate over a specified period of time. The

simulation model was validated using the methods defined by the system dynamics SD methodology according to (Sterman, 2000). Available industry data was also used to the extent that was feasible and possible. The model was calibrated to reproduce meaningful results according to the theoretical development.

4.2.4 Model analysis and results

The sensitivity analysis facilitated the identification of the relevant model parameters. The main purpose of this phase was to test the impact of different interventions (parameter changes) on the model in order to improve the system behavior.

This chapter includes the development of the causal loop diagram and the model formulation and implementation for Stage 1. The model formulation and implementation for Stage 2 is developed in Chapter 5.

4.3 Causal loop diagram

The causal loop diagram included the main elements identified as factors affecting the adoption. These factors were identified through an extensive literature review on data standards literature which was explained in Chapter 3. The factors included in the causal loop diagram are brought from the conceptual model. The transition from the initial list of factors defined in the conceptual model including the grouping of the different elements according to the TOE framework in order to develop the causal loop diagram is explained in this section. The factors are grouped in three categories: environment, technology and organization. Within the environment section, the external factors affecting the adoption are considered. Since the model takes into consideration two perspectives (technology provider and healthcare provider), the

relative advantage is considered for both stakeholders as well as the readiness. There are two known positive relationships not included directly (but indirectly) in the causal loop digram, the size and the top management support; these relationships are considered within the organization section but as part of the organization readiness. The causal loop diagram provides an explanation of the factors affecting the healthcare provider adoption rate. The main elements of the causal loop diagram are shown in Table 11.

Table 11. Causal Loop Diagram factors

Section	CLD Factors
Environment	*Vendor support:* the support from suppliers and distributors related to the initiative of identification standards *Government intervention:* intervention in the form of a regulation related to identification standards adoption *Industry pressure:* pressure from different industry groups to adopt identification standards
Technology	*Technology provider readiness:* readiness level of the technology solution provider towards adoption *Relative advantage (Technology provider):* the relative gain cost/benefit that can be obtained from adoption *Complexity:* complexity of the technology *Interoperability:* the ease of integration of the adopting technology to existing systems
Organization	*Organization readiness (P):* readiness level of the healthcare provider related to the processes and the scope of the adoption *Organization readiness (T):* readiness level of the healthcare provider related to the technological capabilities associated with the adoption *Relative advantage (Hospital):* the relative gain cost/benefit that can be obtained from adoption

The basic structure of the causal loop diagram is the stock flow representation of the healthcare provider population. The healthcare provider population is divided into adopters and potential

adopters, and the transition between the two groups is represented by the adoption rate. Around the adoption rate a word of mouth model (Sterman, 2000) better known as technology diffusion model approach is followed to exemplify the structure of the problem. The arrows and its signs depict the relationships among the factors within the diagram. A positive sign illustrates a proportional change; a negative sign illustrates the opposite relationship (an increase in one factor would have a diminishing impact on the other). As mentioned before, the causal loop diagram takes into consideration two perspectives the healthcare provider perspective and the technology solution provider perspective, and how they both interact with the environment. The sections within the causal loop diagram CLD are identified with three colors as shown in Figure 9. The color blue represents section one; the color green represents section two and the color orange represents section three.

4.3.1 Section one (environment)

Industry pressure

The industry pressure comes from the Group Purchasing Organizations and industry groups. As pointed out by (Barlow, Premier CIO conducting data synchrony. Alliance pushes harder for supply chain data standards, 2009) the pressure from the different industry groups could contribute to speed up the adoption process by increasing the pressure for solution provider readiness. The industry pressure could increase the awareness of the different stakeholders in particular healthcare providers through educational programs about the benefits and ways to adopt the standards.

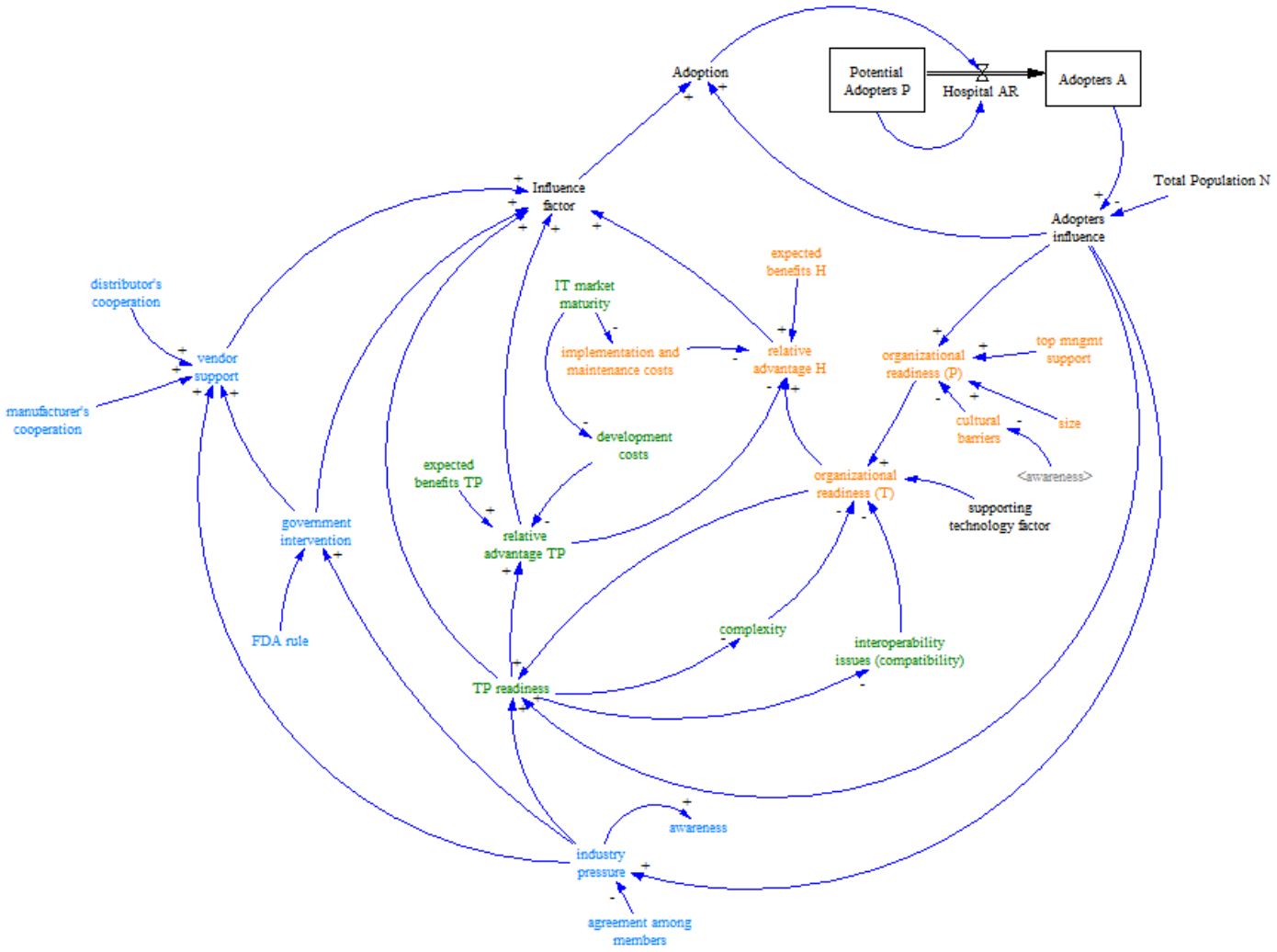

Figure 9. Causal loop diagram.

The awareness is another important component that could drive adoption (Barlow, Sync or swim: Who should blink first and why?, 2007) along with peer pressure can be a strong motivator (Barlow, Crafting the supply chain stimulus package, 2009), as more healthcare providers start realizing the benefits in supply chain operations and patient safety others will follow and the industry pressure would be higher. The industry pressure can contribute to increase the technology solution provider readiness which could help to solve interoperability related issues.

Government intervention

The government intervention could be in the form of a regulation such as the UDI system or through financial incentives provided to stimulate adoption. As pointed out by (Barlow, FDA Negotiates through device data standards stalemate, 2010) the FDA have authority only over manufacturers but not over the healthcare providers or any other healthcare supply chain transacting member. This means that a regulation would be followed by manufacturers and ultimately would lead to an industry wide adoption if other supply chain members participate in the adoption effort. There are different positions regarding the endorsement of a unique set of standards; the government believes that multiple standards could benefit the industry (Barlow, FDA Negotiates through device data standards stalemate, 2010) while a unique set of standards is claimed by some industry groups (Barlow, Alliance subgroup throws down device data standards gauntlet, 2010).

Vendor support

Manufacturers and distributors are transacting members directly related to the product flow and its actions could have an impact in the healthcare provider's adoption rate. The way they use the

technology and the identification standards within their processes and within the processes related to the healthcare provider can drive the adoption at the healthcare provider level. The vendor support element has a direct impact on the influence factor and is directly affected by the industry pressure and government intervention factors.

4.3.2 Section two (technology)

Technology solution provider readiness

Technology solution providers include the MMIS vendor providers and the EDI vendors (for type I processes). The technology solution provider readiness element is influenced by the adopters influence and the industry pressure. The developments of the organization (healthcare provider) regarding its technological capabilities can affect the technology solution provider readiness.

As pointed out by (Barlow, Alliance subgroup throws down device data standards gauntlet, 2010), (Perrin, 2009) this is one of the most critical links preventing adoption: technology solution providers are not ready because hospitals are not requesting the fields to be active or to be transacting with the identifiers, so technology providers are just going to wait. On the other hand, hospitals will not do it because they do not see the direct benefits of its adoption. The technology solution provider readiness is related to the complexity and interoperability factors. In this regard, the technology provider readiness is affected by how complex the solution is to implement; the more complex the less ready the technology provider is. Likewise, the more interoperability issues to be solved, the less ready the technology provider can be.

Relative advantage technology solution provider

The relative advantage of the technology solution provider is influenced by the expected benefits from adoption and the technology development costs. The relative advantage has a direct impact on the influence factor and also on the relative advantage of the healthcare provider.

4.3.3 Section three (organization)

The healthcare provider readiness is defined from the process and technology perspectives.

Organizational readiness (P)

The organizational readiness (P) is the level of readiness of the healthcare provider from the process perspective. It is influenced by the cultural barriers, awareness, the healthcare provider size, the information technology budget and the top management support. The organizational readiness (P) has impact on the organizational readiness (T) (Murphy, 2008).

Organizational readiness (T)

The organizational readiness (T) is the level of readiness of the healthcare provider from the technology perspective. It is associated with the technological capabilities of the organization towards adoption. It is influenced by the organizational readiness (P) and the percentage of supporting technology penetration (Shortliffe, 2005).

Relative advantage healthcare provider

The relative advantage is influenced by the expected benefits from adoption and the associated implementation and development costs (Levine, 2007). The relative advantage of the technology

solution provider is also an important factor since the technology providers would benefit by the investments made by adopting healthcare providers. The relative advantage of the healthcare provider has a direct impact on the influence factor.

The causal loop diagram considers two main stakeholders: the healthcare provider (healthcare provider and hospital are equivalent terms) and the technology solution provider. The impacts of the different elements in the adoption rate along with the relationships among them are illustrated in the causal loop diagram and the main hypotheses are explicitly presented. For example it is assumed that the technological readiness level of the healthcare provider defined as the organizational readiness (T) will have an impact in the technology solution provider readiness, and this element will also increase the relative advantage for the technology solution provider. The causal loop diagram is the systemic explanation of the adoption process. It is similar in its goal to the conceptual model. The CLD provides the starting point for the model formulation and the simulation model development.

4.4 Definition (Identification Standards)

The literature review developed in Chapter 3 revealed that there is not a clear or formal definition related to identification standards, neither there is a consensus related to what adoption means or how an adopter could be defined. The absence of a clear definition could be explained because the identification standards process is a recent adoption process, started in 2008, and also because of the nature of the concept and the complexity associated to its definition. In addition to process changes, the adoption of identification standards accounts for the adoption of a set of technologies, not the adoption of a single technological component.

This section establishes the absence of a clear definition of identification standards. In addition, reference points from the literature are discussed, including the definition of Electronic Health Records EHR. Major similarities and differences between identification standards adoption and EHR adoption are presented. Finally, the proposed definition for Identification Standards (IdS) is explained.

Some examples of the identification standards definitions found from the literature sources are:

- A 2% adoption is given by (DeJohn, 2008) but the author does not specify any definition.
- The survey by (Nachtmann & Pohl, 2009) summarized information related to adoption of identification standards but no specific details about the definition used to gather the data was given in the report.
- The report by (Pohl & Nachtmann, 2011) referred to a system of standards, but no specific definition was given.
- Readiness data was provided on the GS1 website. The website presented the result of the voluntary assessment data dated November 2011 (625 adopting members).

The literature review showed that identification standard was usually referred to as a system of standards. The system of standards concept can be understood as a set of standards that includes the location and product identifiers that are used within a given set of processes. In order to be able to measure to some extent the adoption of identification standards, a clear definition at a specific level of aggregation and process scope has to be established. The level of aggregation is related to the perspective, in this case the healthcare provider, and the process scope is related to the type of processes under analysis.

4.4.1 Related definitions

The adoption of Electronic Health Records (EHR) can be used as a reference point to analyze the identification standards situation. In the case of EHR many authors have agreed that in order to measure the progress of EHR adoption, a consensus must be reached among the main stakeholders and a clear definition should be established (Jha, DesRoches, Kralovec, & Joshi, 2010). The authors defined a basic EHR as a set of 10 clinical functions deployed in at least one hospital unit. According to this definition the data was collected and analyzed. A 9.2% penetration of a basic EHR among hospitals was reported.

There are some similarities, and differences between EHR adoption and identification standards adoption. Both adoption processes are in the same setting, healthcare, but the healthcare provider is at the lead of EHR adoption due to its nature. EHR is a software application exclusive to the healthcare provider. This means that the healthcare provider is the only one responsible for capturing and storing the EHR related information. This is not the case for identification standards adoption where any supply chain member could adopt it. Moreover, the identification standards concept is built into existing software applications used throughout the supply chain; it cannot be defined as a standalone application. This issue in particular represents a challenge related its justification from the ROI perspective (Menachemi & Brooks, 2006).

4.4.2 Conceptual definition (proposed definition)

The definition of identification standards in the context of the present research is a process-technology based definition as it was initially proposed in Section 3.3.1. This definition is based on the assumption that the supporting technology required to make use of the product and

location identifiers would have a key role in explaining the adoption of identification standards. This implies that the adoption of identification standards would be limited by the presence of the required infrastructure to perform the supply chain transactions within a process of a given process scope.

From the healthcare provider perspective it is assumed that there is a specific set of processes performed within the organization using the identifiers. Those processes can be grouped according to its scope as shown in Table 12. It is assumed that each process is composed of a set of transactions. Each transaction is supported by a given technological infrastructure, and each transaction makes use of the identifiers.

Table 12. Identification standards operational definition

Process type	Scope	List of processes / cycles	Supporting technology
I	External link	Ordering	MMIS, EDI
II	Internal	Storeroom operations	Barcode enabled SCM
III	Patient link	Medication administration including supplies	BCMA, BPOC

Processes type I. These processes are performed by the healthcare provider in the context of the external environment. The processes with trading partners include contract/pricing administration and the purchase order to payment cycle, among others. The transactions are assumed to be performed by electronic means with the support of EDI and an application such as the MMIS. The adoption of identification standards in processes Type I assume location and product identifiers use within the relevant processes related to the external ordering cycle, contract management and rebates.

Processes type II. These processes are performed within the healthcare provider and do not involve any trading partner or patient. These processes are associated to inventory management control activities within the main storeroom and the hospital floors. The transactions are assumed to be facilitated by the supporting technology such as a barcode enabled supply chain management application (BC SCM). The adoption of identification standards in processes type II assume location and product identifiers use within the relevant processes related to the hospital internal supply chain.

Processes type III. These processes are related to transactions within the healthcare provider and directly related to patient care at the point of use. The transactions are assumed to be facilitated by the use of the supporting technology such as a BPOC or Barcode Medication Administration (BCMA) application. The adoption of identification standards in processes type III assume location and product identifiers use within the relevant processes related to the administration of pharmaceuticals and the use of medical supplies at the point of care.

The concept of the process technology based definition is illustrated in Figure 10. According to the figure a business process is based on a given set of transactions and within those transactions the corresponding identifiers are used. An adopter is a healthcare provider performing a given transaction using the identifiers and the supporting technology (See dashed line in Figure 10). The operational definition implies that adoption of identification standards can be modeled as the diffusion (external diffusion) of the bundle identification standards-technology across a given population.

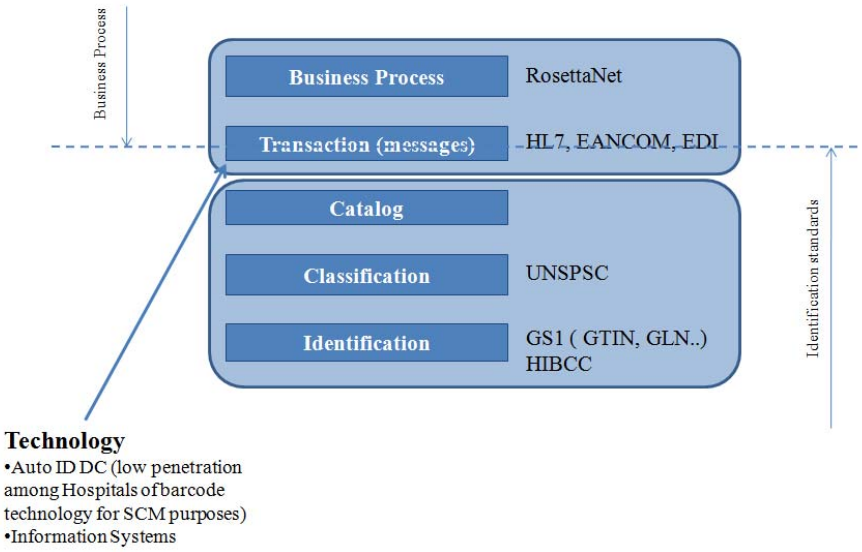

Figure 10. Identification standards definition (adapter from Hubner and Elmhorst, 2008)

This definition has the following implications regarding the model scope. According to classic diffusion theory, the members of a population interact with each other and with the external environment. One of the underlying assumptions of technology diffusion models is that technology acceptance is an imitation process. The members of the population get in contact with each other and with the environment and exchange information related to the innovation (Majahan & Wind, 1986). The technology is first adopted by a select group of innovators who in turn, influence others to adopt it. The innovation (technology) is defined in this case as the supporting technology required to facilitate a set of supply chain related processes within the healthcare provider.

The behavior of the total population as a whole was considered as opposed to a single hospital. There is not a detailed process description but the aggregated population behavior over the proposed set of processes is given. The model does not provide specific details on the identifiers (product and location) but the projection of the use of identifiers among the processes and

transactions performed by healthcare providers is estimated. In an aggregated form (by process group) the adoption of identification standards will be limited to the used of anchored identifiers as defined by (Buyurgan, Rardin, Jayaraman, Varghese, & Burbano, 2011) within the main transactions along the medical-surgical supply chain. The aggregation by process group type is associated to the characteristics of the supporting technology.

As an example of the proposed aggregation, a detail list of processes, basic requirements and transactions for processes within group type I is shown in Table 13. This table is based on the EHCR report (CSC, 1996). As of 1996 the need for location and product identification was explicit, also the basic technological requirements were outlined. For example EDI and MMIS were defined as basic requirements to support supply chain related processes within processes type I as well as the need for location and product identifiers.

Table 13. Identification standards operational definition EHCR

	Process set	Basic requirements	EDI transactions
Type I	Contract/Pricing Administration cycle	Electronic Customer Identification Electronic Product Identification EDI Transactions Sets Policy and process comprehension Member Eligibitily Negotiations Electronic Contract/Pricing Notice Electronic Sales/Rebate Reporting Performance Measures Activity based Costing	816 Organizational Relationships 832 Price/Sales Catalog 836 Procurement Notices 840 Request for Quotation 843 Response to Request for Quotation 845 Price Authorization 867 Product Transfer and Resale Report
	Purchase Order to Payment cycle	Electronic Customer Identification Electronic Product Identification EDI Transaction Sets Electronic Order Management Electronic Shipping and Receiving Electronic Billing Electronic Funds Transfer Activity based Costing Performance Measures	810 Invoice 812 Credit/Debit Adjustment 820 Payment Order 822 Account Analysis 832 Price/Sales Catalog 850 Purchase Order 855 Purchase Order Acknowledgment 856 Ship Notice/Manifest 861 Receiving Advice/Acceptance Certificate
	Sales Activated Settlement	Electronic Customer Identification Electronic Product Identification EDI Transactions Sets Contract Membership Eligibility Electronic Contract/Pricing Notice Shared Databases Performance Measures Activity Based Costing	810 Invoice 816 Organizational Relationships 820 Payment Order 832 Price/Sales Catalog 845 Price Authorization 856 Ship Notice/Manifest 867 Product Transfer and Resale Report

It could be possible to track adoption over time or progress regarding the identification standards adoption among hospitals, but a longitudinal study to measure adoption in terms of the previous definition would be necessary. For example, the perfect order definition could be used, but other definitions among the finite set of transactions and processes must be defined. Adoption could be measured by process, taking into consideration how many processes and transactions are using identification standards. The proposed identification standards definition is ideal because adoption data related to each one of the processes and its corresponding transactions is currently unavailable. The ideal definition development and data gathering can be based upon a process matrix like the one shown in Table 14. Gathering adoption data would require the specification of the scope of the processes being surveyed along with the longitudinal data (at least 3 years). A study of such kind is out of the scope of the current research and modeling efforts.

4.5 Model formulation

Following the system dynamics methodology for phase II, a classical technology diffusion model was selected as the initial model to formulate the adoption process under study. The Bass Diffusion Model (BDM) is used to represent the adoption process and to mathematically describe the adoption rate. The model is focused on the time pattern of the spread of innovation. The BDM and its revised forms have been successfully demonstrated and applied in retail service, industrial technology, agricultural, educational and consumer durable markets (Majahan & Wind, 1986). It has been also recognized that one of the most useful inputs to decision makers, planners and researchers is the temporal pattern of the diffusion process (Sharif & Ramanathan, 1981).

Table 14. Identification standards ideal definition

Process type	Cycle	Basic requirements	Process/area	Tr. Sets	or documents (electronic)	GLN	GTIN	Both used
Type I	Purchase Order to Payment Order to Payment	MMIS in place EDI in place	Purchasing Accounts payable Materials management	812	Credit/Debit Adjustment	can be used	can be used	TBD
				820	Payment Order/Remittance Advice	can be used	can be used	TBD
				822	Account Analysis	can be used	can be used	TBD
				832	Price/Sales Catalog	can be used	can be used	TBD
				850	**Purchase Order**	can be used	can be used	**Perfect order**
				855	Purchase Order Acknowledgment	can be used	can be used	TBD
				856	Ship Notice/Manifest	can be used	can be used	TBD
				861	Acceptance Certificate	can be used	can be used	TBD

4.5.1 Mathematical formulation

The fundamental diffusion model (Mahajan & Peterson, Models for innovation diffusion: Quantitative applictions in the social sciences, 1985) can be expressed as the differential equation:

$$\frac{d\,N(t)}{dt} = g(t)[\bar{N} - N(t)] \qquad (1)$$

With the boundary condition $N(t = t_0) = N_0$, where.

$N(t)$ = cumulative number of adopters at time t

$n(t)$ = non cumulative number of adopters at time t, which means $N(t) = \int_0^t n(t)dt$

$\bar{N}$ = total number of potential adopters in the system at time t (also equal m)

$\frac{d\,N(t)}{dt}$ = rate of diffusion at time t

$g(t)$ = diffusion coefficient

N_0 = cumulative number of adopters at time t_0

The diffusion coefficient is usually expressed as a function of the number of previous adopters as:

$g(t) = a + bN(t) + cN(t)^2 + \ldots$

According to the expression above, the diffusion coefficient can be expressed as:

$g(t) = a$

$g(t) = bN(t)$

$g(t) = a + bN(t)$

Three diffusion models can be obtained by using the previous expressions:

The external influence diffusion model:

$$\frac{dN(t)}{dt} = a[\bar{N} - N(t)] \quad (2)$$

The internal influence diffusion model:

$$\frac{dN(t)}{dt} = bN(t)[\bar{N} - N(t)] \quad (3)$$

The mixed influence diffusion model:

$$\frac{dN(t)}{dt} = (a + bN(t))[\bar{N} - N(t)] \quad (4)$$

The coefficients a and b are known as coefficients of external and internal influence respectively. The coefficient of external influence a represents the influence from outside the system, not related to previous adoptions. The coefficient of internal influence b, represents the influence of the previous adoptions in the form of a contagion rate, and it also represents the interaction of prior adopters with potential adopters. Coefficients a and b also appear in some diffusion models notations as coefficients p and q, but its meaning is the same.

The mixed influence diffusion model described in Equation (4) is also known as the Bass Diffusion model BDM (Sterman, 2000). The work developed by (Teng, Grover, & Guttler, 2002) illustrates the use of the BDM in order to analyze the diffusion of 20 technological innovations and the relationship of technology characteristics in the different diffusion patterns. A resemblance to the mathematical structure of this model is found in (Erdil & Emerson, Simulation modeling of electronic health records adoption in the U.S healthcare system, 2009), but no explicit reference to it is made by the authors. The BDM model is also used by (Bower, 2005), in the analysis of EHR adoption. In this work the author illustrates the potential use of the model but does not proceed with any mathematical estimation of the parameters; instead, the author uses the model to describe the qualitative approximation developed to represent the main forces affecting EHR adoption.

The BDM and conventional parameter estimations

An equation similar to (1) was presented by (Majahan & Wind, 1986) and is suggested for parameter estimation purposes. The equation can be used to represent a given diffusion process as:

$$\frac{dN(t)}{dt} = \left(p + \frac{q}{m}N(t)\right)(m - N(t)) \qquad (5)$$

Where $N(t)$ is the cumulative number of adopters at time t, m is the ceiling, p is the coefficient of innovation and q is the coefficient of imitation. Assuming $F(t) = N(t)/m$, where $F(t)$ is the fraction of potential adopters who adopt the product by time t, the BDM can be restated as:

$$\frac{dF(t)}{dt} = \big(p + qF(t)\big)\big(1 - F(t)\big) \tag{6}$$

If $N(t = t_0 = 0) = 0$, then simple integration of Equation (6) gives the following distribution function to represent the time dependent aspect of the diffusion process.

$$N(t) = m\left(\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}\right) \tag{7}$$

Equation (7) yields the s-shaped diffusion curve captured by the BDM. For this curve the point of inflection, which is the maximum penetration rate $\left[{dN(t)}/{dt}\right]_{max}$, occurs when:

$$N(t^*) = m\left(\frac{1}{2} - \frac{p}{2q}\right) \tag{8}$$

$$t^* = -\frac{1}{p+q}\ln\left(\frac{p}{q}\right) \tag{9}$$

And also the equation:

$$f(t^*) = \frac{dN(t^*)}{dt} = m\left(\frac{q}{4} + \frac{p}{2} + \frac{p^2}{4q}\right) \tag{10}$$

Hence, if p , q and m are known for a particular product, equations (7) – (10) can be used to represent the product growth curve.

A number of estimation procedures have been used for estimating the model parameters (Majahan & Wind, 1986).

- Ordinary least squares (OLS)
- Maximum likelihood estimation (MLE)
- Nonlinear least squares (NLS)
- Algebraic estimation

A detailed description of each one of the procedures is presented in (Majahan & Wind, 1986). The NLS estimation procedure is the one that gives better predictions compared to OLS and MLS (Mahajan, Muller, & Wind, New Product Diffusion Models, 2000). The Algebraic Estimation procedure is explained in the following paragraphs as an illustration on how to estimate the model parameters. This procedure can be used in the absence of sufficient data as in the case of identification standards adoption.

Algebraic Estimation procedure

This method can generate rough estimates of the parameters from knowledge on the occurrence of the point of inflection, as described in the equations listed below.

If the BDM is stated as:

$$f(t) = \frac{dF(t)}{dt} = (p + qF(t))(1 - F(t)) \qquad (11)$$

Since $F(t = t_0 = 0) = 0$, integration of equation (1) yields to:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}} \qquad (12)$$

And by definition

$$N(t) = mF(t) \tag{13}$$

If p, q and m are known for a particular product, then equations (12) and (13) can be used to represent the product's cumulative adoption over time. Equation (12) yields the S-shaped cumulative adoption (diffusion) curve captured by the BDM. The point of inflection for this curve occurs at time t^* and corresponds to the maximum penetration rate $(f(t))_{max}$.

For simplicity, the case of annual sales data is considered so that $t_i = i$ (Majahan & Wind, 1986). The non cumulative number of adopters at the point of inflection t^* is defined as n^* and the cumulative number of adopters at t^* is defined as N^*. Given those definitions equations (8) – (10) can be rewritten as:

$$\frac{N^*}{m} = \frac{1}{2} - \frac{p}{2q} \tag{14}$$

$$t^* = -\frac{1}{(p+q)} \ln \frac{p}{q} \tag{15}$$

$$\frac{n^*}{m} = \frac{q}{4} + \frac{p}{2} + \frac{p^2}{4q} \tag{16}$$

If N^*, n^* and t^* are known, then equations (14)-(16) can be re written as:

$$p = \frac{n^*(m - 2N^*)}{(m - N^*)^2} \tag{17}$$

$$q = \frac{n^* m}{(m - N^*)^2} \tag{18}$$

$$t^* = \frac{(m - N^*)}{2n^*} \ln\left(\frac{m}{m - 2N^*}\right) \tag{19}$$

This way, equation (19) can be used to find *m* numerically. Once *m* is known, equations (17) and (18) can be used to estimate *p* and *q*. On the other hand if n^* and $t^*$and *m* are known, then equation (19) can be solved to find *N**; finally *p* and *q* can be estimated from equations (17) and (18).

The algebraic estimation procedure is conceptually simple, but it requires information regarding the point of inflection. Researchers (Majahan & Wind, 1986) suggest that in the absence of any data, management can make educated guesses about *t**, *n** and *m* (or *N**) based on analogous products so that diffusion curves can be developed for the technology under study.

4.5.2 Bass Diffusion Model parameters and CLD factors

The classic diffusion models represent a way to understand the diffusion process but are limited by the need for data on past adoptions (Nelson M. J., 1998), (Mahajan & Peterson, Models for innovation diffusion: Quantitative applictions in the social sciences, 1985). Classic diffusion models work under the assumption that enough data on past adoptions is available in order to feed closed forms and thus estimate the parameters following conventional estimation procedures (Mahajan, Muller, & Wind, New Product Diffusion Models, 2000). This represents a challenge from the identification standards perspective.

For identification standards (based on the definition given in the previous section) the adoption data is currently unavailable. In order to collect the information, it would be necessary develop and deploy and instrument for data collection in order to construct the data set. This research contributes to the understanding of the identification standards adoption process by proposing a way to address the problem of lack of adoption data and a consensus on a clear definition. The

formulation stages are proposed as a way to overcome those challenges and the operational definition given in the previous section is proposed as a way to guide modeling efforts, in particular for Stage 2.

The use of system dynamics in diffusion modeling has been attempted in previous studies. Initial explorations of the use of the methodology are presented by (Finkelstein, Homer, & Sondik, 1984). The work developed by (Maier, 1998) is specifically related to Stage 1 and the work developed (Erdil & Emerson, Simulation modeling of electronic health records adoption in the U.S healthcare system, 2009) and (Nelson, 1998) is related to Stage 2.

4.5.3 Formulation stages

The formulation stages were developed to learn about the behavior of the model parameters and to overcome the challenges related to the identification standards definition and also the lack of data on past adoptions. The model formulation follows a two stage process. Stage 1, or initial approach, in which the BDM is used to mathematically describe the adoption process. Stage 2, or second stage includes the relationships as established in the CLD and represents the empirical relationships within all the factors defined in the CLD.

Stage 1 - Initial approach

The initial approach works under the assumption that the diffusion of the supporting technologies can help to explain identification standards adoption and diffusion.

The goal of this stage is to estimate the BDM parameters, p and q, for the given set of supporting technologies associated to the identification standards definition. The discrete version of the

formulation BDM is used to estimate the model parameters and to solve the model analytically with methods described in Section 4.5.1. It is important to note that the CLD described relationships are not used in this approach, just the model parameters associated to the internal and external diffusion coefficients *p* and *q*.

Stage 2 – CLD relationships based model

The empirical development of the relationships between the factors and the BDM coefficients was established, and then the formulation of the factors was developed; in this case, no mathematical or closed solution exists.

The goal of this stage is to develop a model that simulates the adoption rate over time (diffusion) and to observe the impact of the internal and external influence coefficients in the adoption rate. The model is developed to simulate the diffusion of identification standards across the hospital population over time. The sum (cumulative) adoption through time represents the diffusion. It has been reported that the estimation of the exact nature of the interactions between the different factors can be very difficult in many situations (Maier, 1998), (Sharif & Ramanathan, 1981).

Scope

Healthcare provider perspective is considered and a specific definition of the technology to be defined as "adopted" has to be assumed. In the context of this research (stage 1) adoption is defined as the level of penetration of a given technology (supporting technology) and diffusion is defined as the widespread adoption of the technology among the members of a given population. For stage 2, the level of penetration or adoption (identification standards-technology bundle) has

to be established using available industry data and the diffusion process is modeled via simulation.

Limitations/assumptions

The advantages and limitations of the system dynamics modeling approach and the BDM diffusion model as the basic structure of the model formulation have to be considered. As for the modeling approach, there is not a detailed level of granularity at the healthcare provider level, but an aggregation at the population level is assumed. A further breakdown into smaller sets (large and small hospitals) could be considered, along with the inclusion of additional supply chain members (e.g. population of distributors and manufacturers).

As for the BDM diffusion model, the healthcare provider population was considered as the main component of the model. The healthcare population was divided between adopters and potential adopters, also the impact of the external and internal influence coefficients in the adoption rate was assumed. The existence of past data (Stage 1) is assumed based on the supporting technologies due to the lack of data on identification standards past adoptions. The model goal (Stage 2) is to conceptualize the adoption process of identification standards in a higher level of abstraction; some of the structural components of the model are presented in an aggregated form. The advantages of the systems dynamics approach over traditional linear models are that the model captures the impact of the interventions, it helps to represent the system along with the causes, and it provides an insight on the behavior of the adoption rate. The purpose is not to forecast but to understand the system behavior. As explained by (Majahan & Wind, 1986), one of the most important uses of diffusion models is to provide an analytical approach to describe

the spread of diffusion phenomena. As such, they can be used in exploratory mode to test specific diffusion based hypothesis or to explore system interventions.

4.6 Stage 1 – model formulation, implementation and validation

Due to the lack of data on identification standards past adoptions, the supporting technology approach is used to understand the identification standards adoption process. The healthcare provider is considered as the population under study for modeling purposes. It is assumed that the behavior of the diffusion of the technology that supports identification standards use is key to understand identification standards adoption and diffusion.

4.6.1 Model formulation (Stage 1)

For Stage 1 the basic structure of the Bass Diffusion Model BDM is used. The BDM depicts the rate of change in the number of adopters over time, and it illustrates the impact of the internal and external diffusion coefficients in the adoption rate.

The model allows for an analysis of the evolution of the adoption rate over time. Based on the analysis of this path, the peak (inflection point) can be established as well as the growth and stabilization periods. The impact of the diffusion coefficients it is also subject to analysis. An illustration of the model in Vensim is presented in Figure 11. The adoption rate represents the flow between the potential adopters and the adopters (population under study), and the external and internal diffusion coefficients are represented by p and q respectively.

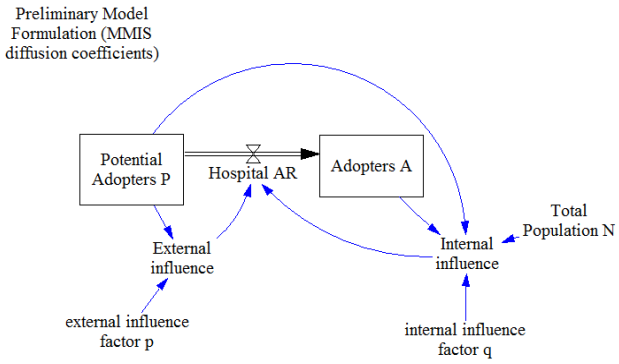

Figure 11. Stage 1 – Vensim Model

Parameter estimation

There are different strategies that can be followed in order to estimate the model parameters. For this formulation stage, two strategies were followed in order to obtain information related to the model parameters:

a. By analogy, following the work developed by (Teng, Grover, & Guttler, 2002) and (Mahajan, Muller, & Wind, New Product Diffusion Models, 2000).
b. With data on adoption of supporting technologies by process (healthcare) and then following estimation procedures previously defined, using the discrete analog of the BDM.

4.6.2 Parameter estimation - analogy approach

The analogy approach is based on the assumption that analog technologies could provide an starting point for parameter estimation due to the lack of available data on identification standards past adoptions. In order to estimate the model parameters (base run) the parameter values described by (Teng, Grover, & Guttler, 2002) for technologies within cluster two were

used. For this type of technologies the average values of *p* are low (0.003) and the average values of *q* are higher (0.38). For the current model *p* is 0.003 and *q* is assumed to be 0.25 which is the median value in the table of page 22 from the reference document (Teng, Grover, & Guttler, 2002).

The model formulation was implemented in Vensim, and the output results were obtained using the report options. In order to use the BDM the adopting population was assumed as the total number of hospitals registered in the AHA (5500 hospitals). The population was considered homogenous, and no new hospitals were going in or out of the system. The periods within the model were defined as years. The starting year was assumed as 2008, and the horizon was defined as 50 periods (years). The values for *p* and *q* were used to test the model under for different scenarios. Scenario 1 (S1) considered the 2% adoption rate given by (DeJohn, 2008) with an initial population of 110 healthcare providers. Scenario 2 (S2) did not contemplate any initial population. Scenarios 3 and 4 were variations of the initial year for analysis purposes. Scenario 3 (S3) included the initial year as 1996 which was the year of the publication of the EHCR report. This report marked a point in healthcare industry which brought awareness and established the importance of the required technological infrastructure and identification standards to improve the supply chain related processes. Scenario 4 (S4) included the initial year as 2011.

The only relevant difference among scenarios is the change in the time it takes for the adoption rate to peak. One of the most important observations also is that under the assumed conditions the current deadlines established by the industry cannot be met. There is a deadline for year

2012 on product identifiers adoption and the location identifiers deadline adoption of 2010 already passed. The summary of results is presented in Table 15.

By using the parameters (*p*,*q*) based on analog technologies and available literature sources it was observed that the model could be used to assess the current deadlines for data standards adoption. It would take at least 15 years to reach the saturation point and a critical mass of approximately 2871 healthcare providers. The critical mass concept was referenced by some authors (Barlow, Crafting the supply chain stimulus package, 2009), (DeJohn, 2008). According to (Rogers, Diffusion of Innovations, 1983), the critical mass occurs at the point at which enough individuals in a system have adopted an innovation so that the innovation's further adoption rate becomes self-sustaining; under current conditions it was possible to establish what would be the critical mass for identification standards adoption.

Table 15. Analogy approach results

		Analogy approach			
	Source	initial (DeJohn)	no A0	EHCR date	from today
Scenario	Label	S1	S2	S3	S4
Main inputs	Y0	2008	2008	1996	2011
	Horizon	50	50	50	50
	N	5500	5500	5500	5500
	A0	110	0	0	0
	P	5390	5500	5500	5500
	p	0.003	0.003	0.003	0.003
	q	0.25	0.25	0.25	0.25
Main Outputs	Inf. Point (year)	2022	2026	2014	2029
	Years to AR peak	15	19	19	19
	AR max (H/year)	350.97	352.05	352.05	352.05
	Critical mass (H)	2871	2723	2723	2723

The current results are limited because of the assumptions made regarding the relationship among the technologies described in (Teng, Grover, & Guttler, 2002). The technologies under cluster two are not directly related to healthcare but the results from this approach give an estimate of the time it could take for identification standards adoption to reach a critical mass. Also provides an indication of the number of healthcare providers per period that would be required to join the initiative in order to keep the adoption process on track.

4.6.3 Parameter estimation - supporting technology approach

The model parameters (p,q) can be also estimated by the use of analog technologies within the healthcare domain. The operational definition indicates the required technological infrastructure to support data standards adoption and use within the healthcare provider. In this section, the adoption of the technologies required to support supply chain related processes were studied; those technologies are illustrated in Figure 12.

Each process group type has a set of technologies. For example, processes type I can make use of EDI, processes type II can make use of barcode enabled applications and processes type III can make use of BPOC technology. The MMIS is the underlying platform for technology integration along the internal healthcare provider supply chain.

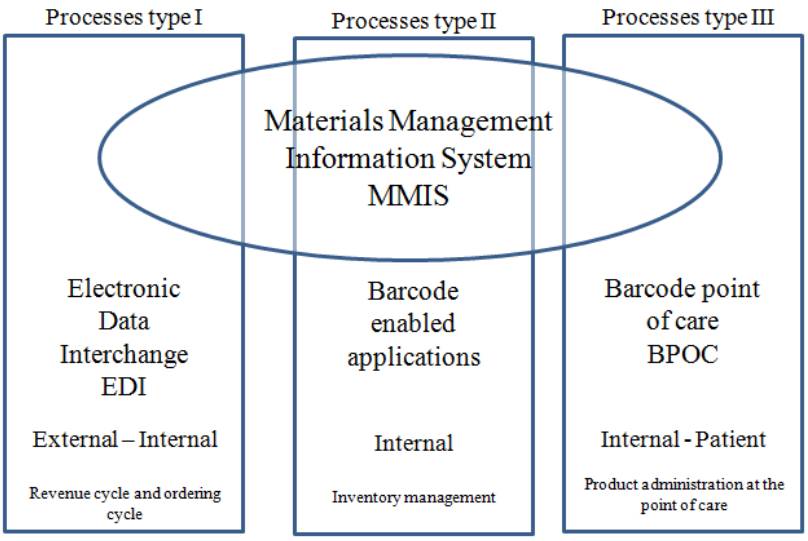

Figure 12. Technology map

Baserun values

The data available through the HIMSS academic agreement which gave access the Dorenfest Institute Data Base was explored. The goal was to estimate the BDM parameters for the supporting technologies related to each process group type.

The available information was analyzed and categorized according to the similarities of the explored databases. The information related to technology adoption among hospitals was collected with an annual survey. It was observed that as the number and scope of questions in the annual survey was expanded some modifications in the compilation of the information was required. For example the earliest versions of the database included information related to the hospital population when the population size was about 3000 hospitals. It was also observed that the information associated to technology availability by database was also different. These

differences led to the categorization of the data bases as shown in Table 16. A detailed list of the available databases is provided in Appendix B.

Table 16. Databases (information sources)

Data base description	Date range	Main characteristics
3000+ DB	1986 -1994	Two sub sets of data, MM year of adoption not software provider information
IHDS DB	1998-2004	Data on several hospital applications, MM year of adoption not software provider information
Complete DB	2005-2007	MM year of adoption and software provider information
2008 DB	2008	Auto identification use/adoption information

After reviewing the available information and classifying the available databases, Micro Soft Office (MSO) Access routines were developed in order to design queries that allowed for the construction of the specific data sets so that BDM model parameters could be estimated. One data set per technology, according to the technology map given in Figure 12 was developed. The tool presented in Chapter 12 of the book by (Mahajan, Muller, & Wind, New Product Diffusion Models, 2000) was used to estimate the BDM parameters. The model parameters were estimated using Nonlinear Least Squares (NLS) method. The tool is a free student version of ME software which runs as an MSO Excel add on. A description of the tool and the supporting information associated with the estimation of the parameters are included in Appendix B.

The model formulation was implemented in Vensim using the model parameters obtained for each technology in order to model the adoption rate behavior. The Stage 1 Vensim formulation of the model is described in Appendix C. Patterns for each technology were obtained and the results are shown in Figure 13.

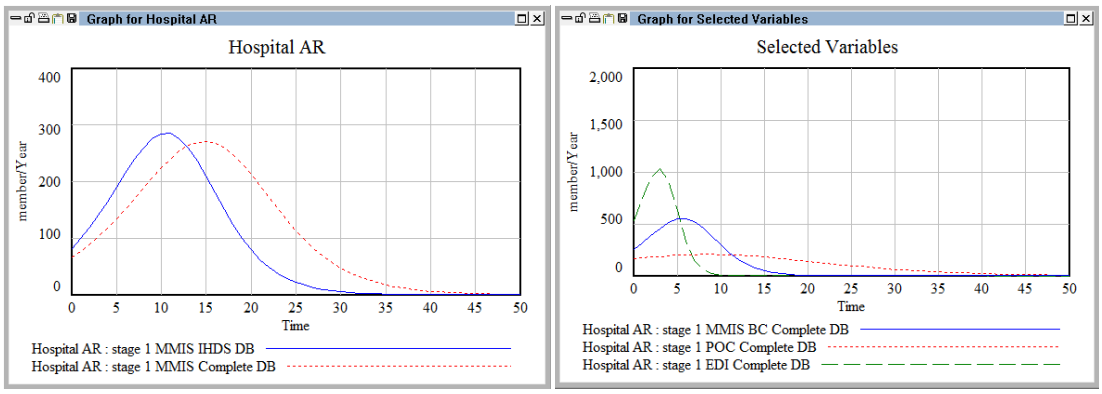

Figure 13. Supporting technology adoption patterns

The model check and units check testing functionality of Vensim was used to validate the models.

The estimation of the model parameters was more reliable for the MMIS technology since there was enough information to develop more than one data set as shown in Table 17. According to (Mahajan & Peterson, Models for innovation diffusion: Quantitative applictions in the social sciences, 1985) at least three data points are required for parameter estimation purposes. The information related to the use of Auto identification technologies for supply chain management purposes among hospitals was relevant after the 2005 HIMSS Data Base (DB) version. Previous versions did not include that type of information. Among the available databases, the 2008 HIMSS DB was the one with the most complete source of information related to the use of Auto ID DC (barcode and RFID) within the hospital population under study. For the adoption of technologies that build upon the MMIS, such as BPOC, the available information was not enough, as there were just three data points available for parameter estimation. Those data points correspond to the data obtained from the 2008 HIMSS DB.

Table 17. Supporting technology approach

		HIMMS DB					
		MMIS			EDI	AutoID DC	BPOC
Source	Data points	10 (1979-1988)	12 (1990-2001)	15(1990-2004)	3(2005-2007)	3(2005-2007)	3(2005-2007)
	Data base	3000+ DB	IHDS DB	Complete DB	Complete DB	Complete DB	Complete DB
	Label	Data Set 1	Data Set 2	Data Set 3	Data Set 4	Data Set 5	Data Set 6
Main input	Y0	1979	1990	1990	2008	2008	2008
	Horizon	50	50	50	50	50	50
	N	3000	4500	5500	5500	5500	5500
	A0	137	265	130	631	831	20
	P	2863	4235	5370	4869	4669	5480
	p	8.94E-18	5.08E-03	8.03E-03	8.43E-17	7.93E-17	3.03E-02
	q	0.3822	0.2437	0.1809	0.4708	0.3155	0.0819
Main output	Inf. Point (year)	1988	2001	2005	2011	2014	2017
	Years to AR peak	9	11	15	3	6	9
	AR max (H/year)	286	284.81	271.22	1032	549	205

The information from the 2008 HIMSS DB was analyzed in order to explore hospital population characteristics such as hospital size, IT budget, operating expenses and technology penetration levels. Since this database had the most complete Auto ID DC related adoption data, the information provided by this database was used to support the development of the formulation of the model in Stage 2.

4.7 Conclusion

The answer of the research question number four is presented. The BDM was used to explore the diffusion of analog technologies as well as the supporting technologies adoption and diffusion (Stage 1). Through this exploration, the groundwork required to estimate internal and

external diffusion coefficient parameter ranges is provided in order to move into the development of the simulation model in the next chapter (Stage 2). Some of the limitations with the use of diffusion models such as the BDM are the need of extensive amount of data on past adoptions to better estimate the parameter values and also the need of a clear definition of the technology to be adopted. A proposed solution to the lack of definition was the operational definition by process type based on supporting technology assumption. Additionally, the formulation stages 1 and 2 were proposed to overcome the lack of past data on identification standards adoptions.

Following the results from the Stage 1 formulation, the adoption patterns for the main technologies for each supporting technology at each process type grouping were found.

The behavior patterns were developed using the data from the HIMSS DB. This database provided information related to the state of technology use by healthcare providers. It was possible to extract relevant data from it by using the tables and designing queries in MSO Access. The data was analyzed further using MSO Excel. The estimation of the model parameters followed the Nonlinear Least Squares NLS estimation procedure. The values of the internal and external diffusion coefficients vary, but certainly p is low and q is higher. The numerical ranges are close to zero for p and the q range is [0.18-0.38]. There are limitations with current data for technologies different than MMIS as there are fewer data points which mean that the results from the parameter estimation are less reliable.

Each one of the supporting technologies exhibits a different adoption pattern or behavior. As shown in Figure 13a, the MMIS diffusion pattern exhibits a peak at year 15. This timeline is close to the ten year timeline estimated by (Langabeer II, 2008) for the diffusion of healthcare

supply chain technologies. Based upon the assumption that an analogy between identification standards and MMIS technology can be established, it can be inferred that the adoption of identification standards could take as long as it took hospitals to adopt its main supporting technology. According to Figure 13b the supporting technologies for processes type I adopt at a higher rate than the supporting technologies for processes type III. Thus, identification standards could be adopted sooner within processes Type I compared to processes type III.

A partial answer to research question number five was also addressed in this chapter. As presented by (Finkelstein, Homer, & Sondik, 1984), the cost is not a relevant issue in the present model due to the fact that the main technology investment has already been made (supporting technologies) and it only requires an upgrade. In contrast, the analysis presented by (Erdil & Emerson, Simulation modeling of electronic health records adoption in the U.S healthcare system, 2009) for EHR adoption presented the cost as one of the most relevant issues. The model developed in this research maintains the assumption presented by (Finkelstein, Homer, & Sondik, 1984), meaning that the costs associated with identification standards adoption are also associated with investments that were already made by hospitals, in particular the MMIS investment. There is a challenge in the estimation of the ROI of most healthcare related investments as presented by (Menachemi & Brooks, 2006). The purpose of the model is to understand the adoption process over a time horizon (50 years) taking into consideration the aggregated benefits that could be obtained from identification standards use within processes at the healthcare provider level.

This research extends the work of (Erdil & Emerson, Simulation modeling of electronic health records adoption in the U.S healthcare system, 2009) related to the adoption of EHR, in the sense

that presents a formal treatment to the mathematical structure that supports the model development. It introduces the system dynamics SD methodology using the information from the conceptual model and develops the mathematical structure of the model based on the available data and the proposed identification standards definition, which poses a challenge. This research brings the results of phase I into a model for phase II, which is a first model of its kind.

5. Model formulation, implementation and validation (Stage 2)

5.1 Model formulation (Stage 2)

The purpose of the model in this formulation stage is to gain insight into the factors that might influence the pattern of identification standards diffusion among healthcare providers (population) and how that pattern could be modified or influenced, as opposed to making predictions or forecasting the future. According to (Rogers, Diffusion of Innovations, 1983) adoption is defined as specific point in time measurement of technology use (usually percentage of adopters), and diffusion is generally understood as the widespread use over time. The goal of the simulation model is to simulate the diffusion (assumed implementation and use over time) of the proposed definition of identification standards. In the context of this research, identification standards adoption is defined as the adoption of location and product identifiers within transactions and processes at the healthcare provider level according to the definition given in Section 4.4. The use of such identifiers would improve the process efficiency; which means less error and fewer resources would be devoted to the processes. There could be also an increase in patient safety due to an improved product administration.

Data in numerical form, industry experts' knowledge and the author's experience are important elements in the formulation development. The primary source of data is the HIMSS DB (2008 version) and information from the literature review on identification standards adoption developed in Chapter 3. That information was used to develop the model assumptions in the form of graphical functions with the support of Vensim functionality. That information was also used to develop the input parameters (base run) as described in the model implementation section.

5.1.1 Simulation model structure

There is a connection between the factors defined in the causal loop diagram (CLD) and the main elements of the simulation model, as shown in Table 18. The factors defined in the CLD were used as a main guideline for the formulation of each simulation model component. For example, the formulation of Component 1 (C1) represents an interpretation of the factors within the environment section which attempts to mathematically express the effect of the external factors on the adoption rate. There are four model components. The factors from the environment section of the CLD were used to formulate Component 1 (C1) of the simulation model. In a similar way, the factors within the technology section were used to formulate Component 2 (C2) and the organizational factors were used to formulate Component (C3). The basic structure of the simulation model is the healthcare population which was included in the model as Component (C4).

Generic model

The generic model is illustrated in Table 19. The formulation of each component was developed taking into consideration the main relationships within the model elements which can be adjusted according to the specific requirements of the population to be analyzed (e.g. hospitals within a network or single hospitals). The models in Stage 1 were developed taking into consideration a single population and each one of the technologies within each process group type. For example, one model for EDI was developed based on BDM parameters estimated as explain in Section 4.6.1. For Stage 2, two populations can be considered although just one of the populations (H>2) is considered for model development and analysis purposes, the assumption of the population size is considered within Component 4 (C4). Component 1 (C1) represents the

environment related factors as a whole while Component 2 (C2) and Component 3 (C3) represent the effect of the average technology provider and healthcare provider respectively.

Table 18. Transition table

Causal Loop Diagram Factors affecting adoption			Simulation model Graphical functions and parameters		
E	1	*Industry pressure*	gf	C1	distributors and GPOs
E	2	*Government intervention*	gf	C1	distributors and GPOs influence
E	3	*Vendor support*	gf	C1	industry pressure
T	4	*TP readiness*	gf	C1	manufacturer influence
T	5	*TP Relative advantage*	gf	C1	manufacturers
T	6	*Interoperability*	p	C1	government intervention
T	7	*Complexity*	gf	C2	technology providers
O	8	*H Relative advantage*	gf	C2	TP expected costs
O	9	*Organization readiness (P)*	gf	C2	TP readiness
O	10	*Organization readiness (T)*	gf	C2	TP relative advantage
			p	C2	complexity and interoperability issues
			gf	C3	H relative advantage
			gf	C3	process fraction
			gf	C3	productivity improvement factor
			p	C3	average H operating expenses
			p	C3	average H revenue
			p	C3	awareness
			p	C3	H technology penetration factor
			p	C3	IdS factor
			p	C3	increase SCM expending
			p	C3	IS Budget
			gf	C4	H IdS Use
			p	C4	A initial
			p	C4	external influence N
			p	C4	internal influence N
			p	C4	P initial

Challenging issues with data

Currently there is no data on past adoptions for identification standards nor information related to the factors as defined in the CLD. The data on past adoptions of identification standards could be used to estimate the BDM parameters (Stage 1) but since the data is not available the estimation and quantification of the model (Stage 2) initial conditions was supported by literature sources and available data. This process was difficult due to the qualitative nature of some of the factors identified in the CLD and in general the data availability (Glöber, Thun, & Milling, 2008). For this reason, gathering and finding qualitative and quantitative data to support the factors in order to describe them in a mathematical form was challenging.

This modeling stage presented a way to analyze the identification standards adoption process, taking into consideration the challenges posed by the data availability, and then proposed a way to overcome those challenges. Since there is no data on the factors, the main factors were transformed into graphical functions (variables) defining a set of parameters to conceptualize and develop the simulation model with the use of the Vensim functionality. The information required to specify the shape and the values for the graphical functions can be obtained from different sources such as industry reports, fieldwork and expert interviews (Sterman, 2000). The graphical functions and parameters are shown in Table 18.

Table 19. Generic model

Stage 1

Models	Assumptions	Parameters BDM	Proxy= IdS
MMIS	one population	*p* *q*	MMIS as the underying infrastructure
EDI	one population	*p* *q*	proxy type I EDI
BC SCM	one population	*p* *q*	proxy type II BC SCM
BPOC	one population	*p* *q*	proxy type III BPOC

Stage 2 (generic)

Model	Model components and assumptions	
IdS H>2	C4 N=3056	C1 (General) C2 (Average tech. provider) C3 (Average hospital) assumptions = gf
IdS H=1	C4 N=2112	C1 (General) C2 (Average tech. provider) C3 (Average hospital)

A cross sectional analysis (survey), at one point in time, could be used to validate the proposed functional relationships (graphical functions) and the model parameters but a questionnaire based on the qualitative nature of the factors could be developed along with the transformation of such qualitative information into a numerical form via fuzzy logic as proposed by (Liu, Triantis, & Sarangi, 2011). Such a project is out of the scope of the current research. A preliminary validation of the proposed model structure and the behavior of the main functional relationships was performed with industry experts. In general the model structure was found coherent and no factors were considered out of the scope.

5.1.2 Model components (formulation)

In this section each component, its main variables (graphical functions), intermediate variables and important parameters are explained. The process followed to implement the simulation model is described in the next section. The main model components are illustrated in Figure 14. The graphical functions and parameters within each component are shown. The description of the graphical functions and parameters is given in Appendix C. The components are used to illustrate the implicit relationships of the CLD factors with the adoption rate.

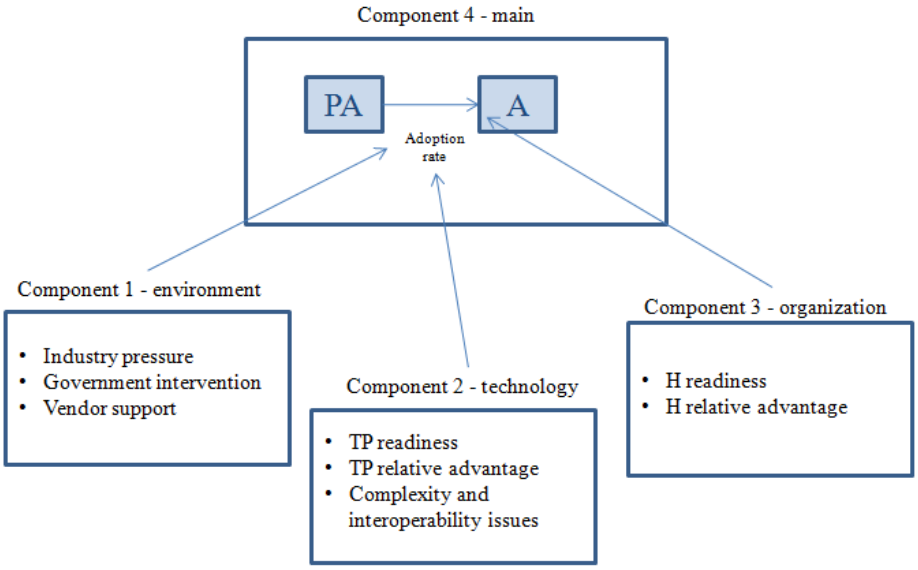

Figure 14. Model components

Component 1 – Environment

This model component is related to the external forces affecting the adoption; it is also related to the stakeholders that make decisions that are out of the control of the healthcare provider.

According to Table 18, the main factors of the environment section in the CLD diagram are the following: vendor support, industry pressure, and government intervention. Those factors are considered within this component as 3 main graphical functions and one parameter. There are two additional graphical functions which are used to represent the manufacturer and the distributor and GPOs populations.

According to the CLD, the vendor support is related to the support of the identification standards initiative from the trading partners such as manufacturers, distributors and GPOs. The vendor support is formulated as a function of the number of healthcare supply chain members adopting the solution. For the simulation model, two separate functions were defined. The first one, is the

manufacturer influence and the second one, is the *distributor and GPOs influence*. This was done due to the fact that the manufacturer population is the only one to be directly affected by any government regulation and the other supply chain members have the option to follow the regulation or to wait until manufacturers implement the required changes. This way the manufacturer population can be affected by a government intervention since manufacturers are the only supply chain members that the government can affect directly via a FDA regulation.

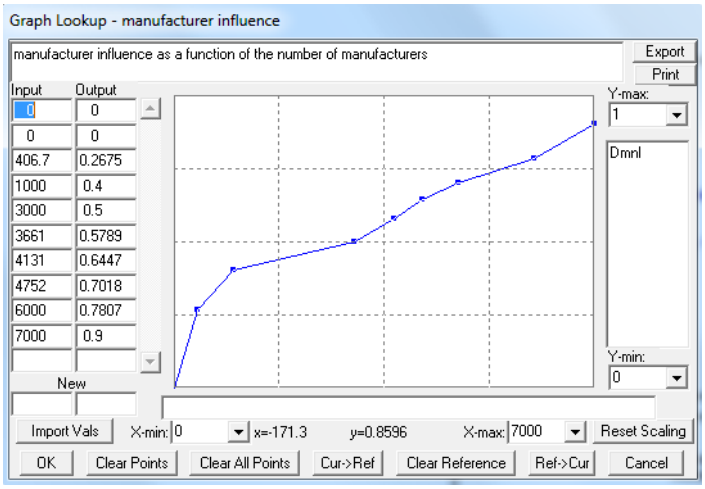

Figure 15. Manufacturer influence

It is assumed that the number of vendors increases over time and so does the influence. The data to support the population size for the manufacturers, the distributors and GPOs was gathered from the Health Industry Distributors Association (HIDA) website and it represents the general medical surgical supply chain. There are about 7000 companies within the US medical equipment and supplies industry, and there are about 200 distributors and GPOs. An increase in the output (influence) was estimated as the number of members joining the initiative increases. The influence is formulated as an increasing function over time but never reaching the limit of 1 as a total output.

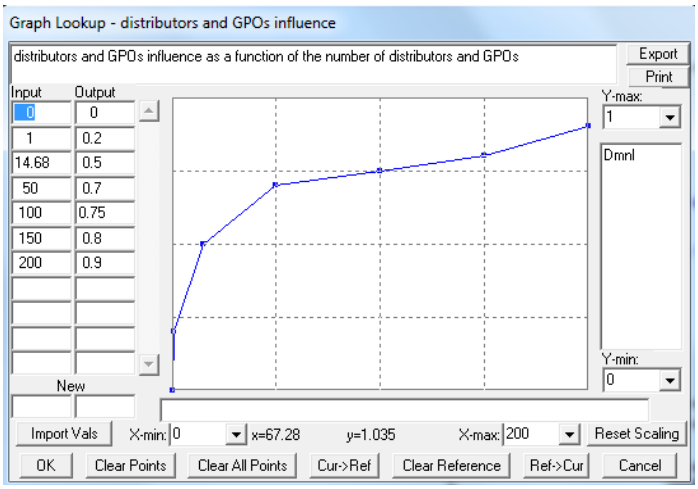

Figure 16. Distributors and GPOs influence

The *industry pressure* reflects the impact that the pressure of industry groups could have on the healthcare provider adoption. It is formulated as a graphical function in Vensim using the influence exerted by distributors and GPOs as the main input. The *industry pressure* is formulated as an increasing function related to the influence exerted by the distributors and GPOs.

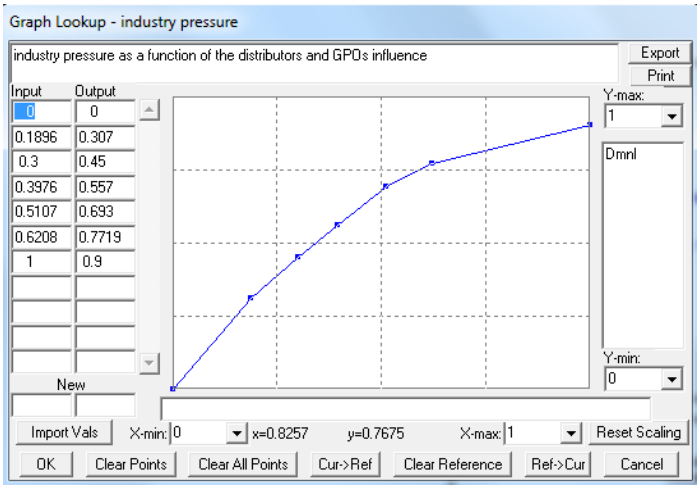

Figure 17. Industry pressure

The *government intervention* factor is related to the pressure that can be exerted through a FDA regulation. Such regulation will have a direct impact on the manufacturers but an indirect impact on healthcare providers via vendors and industry groups.

Currently, the FDA UDI rule is pending. This rule would require the identification of the product in the form of a barcode using either standard (GS1 or HIBCC) and it should also be human readable. This regulation will have an impact only on manufacturers. To notice also that the effect of the regulation would make manufacturers work on product identifiers by product class, starting with the most critical ones. The change will not happen overnight, even if the ruling is released in the near future, it would take time for the manufacturers to comply. It is assumed that even if product identifiers could be available tomorrow (product shipped out of the manufacturer's warehouse with product identifier labels), it will take as long as it took healthcare providers to adopt the supporting technology (MMIS), for identification standards to be used at the healthcare provider level. This assumption is based on the association identification standards - supporting technology which was made in order to analyze the adoption process since no data associated to identification standards past adoptions exists.

The *government intervention* is formulated as a STEP function in Vensim. This function is defined with two parameters the size of the jump and the period. It is assumed in the model that the regulation will be in effect within the next 5 years.

Component 2 - Technology

This model component is related to the technology solution provider and the technologies they provide (supporting technologies) and how the implementation of these technologies would

affect the adoption of identification standards. Identification standards is not a standalone application but a complex concept that requires the incorporation of a set of technologies among a given set of processes at the healthcare provider level as explained in the identification standards definition (Section 4.4).

According to Table 18, the main factors of the technology section within the CLD diagram are the following: technology provider readiness, technology provider relative advantage, complexity and interoperability.

Those factors are considered within this component and formulated using four graphical functions and one parameter. The graphical functions are associated with the technology provider readiness (*TP readiness*), the technology provider relative advantage (*TP relative advantage*), the technology provider expected costs (*TP expected costs*) and the technology provider population (*technology providers*). The complexity and interoperability factor defined in the CLD is formulated as one parameter affecting the technology provider readiness (*TP readiness*).

The technology provider readiness (*TP readiness)* is defined as the preparedness level from the technology solution provider perspective. This factor is related to the willingness to implement the requests made by healthcare providers regarding product enhancements and improvements related to transaction capabilities using identification standards. *TP readiness* is formulated as a function of the number of technology providers joining the initiative over time. It is assumed that the number of technology providers joining the identification standards initiative increases over time and in the same way the readiness increases. The data to support the technology provider population size was gathered from the analysis of the reports developed using

information extracted from the 2008 HIMSS DB. There were about 70 technology solution providers according to the report of solution providers within the supply chain related technology market.

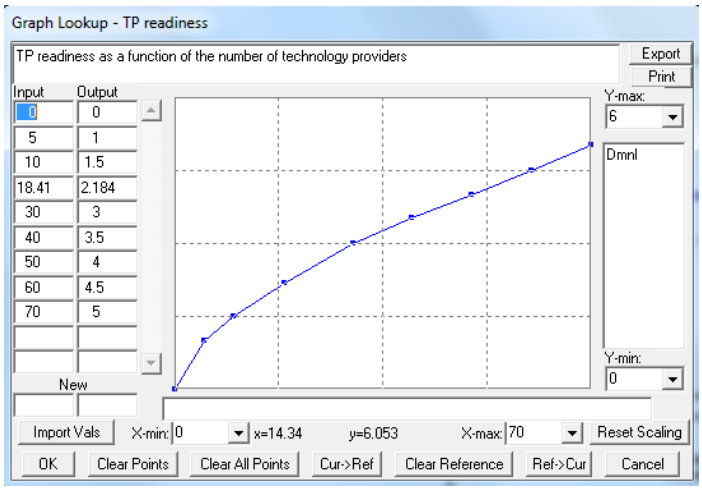

Figure 18. Technology provider readiness

From the technology provider perspective, the technology provider relative advantage is related to the costs and benefits that could be obtained when delivering technology products that meet the requirements associated with identification standards use in the industry. The costs are related to the development costs. It is expected that the costs of development decrease with time. The benefits are related to upgrades of IT products offered to healthcare providers. It is expected that the benefits increase with time. It is assumed that the benefit for the technology provider is the implementation cost for the healthcare provider.

In general the relative advantage is associated with the expected gain that the technology provider could obtain from the delivery of products meeting the requirements. As the gain

increases, the relative advantage increases as well. The gain is defined as the difference between the benefits and the costs.

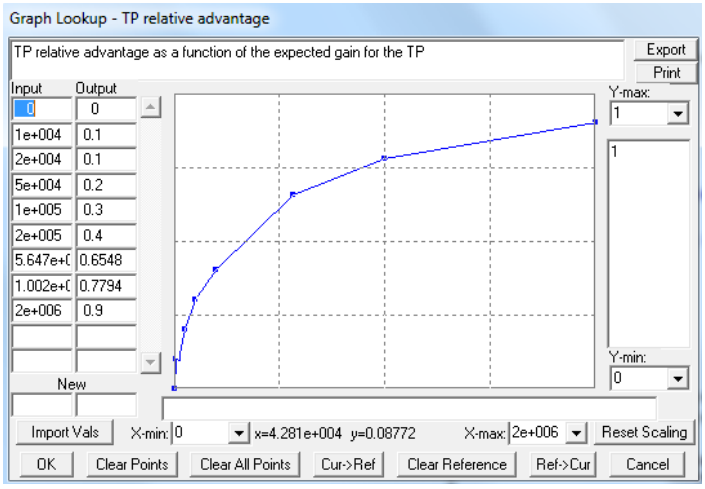

Figure 19. Technology provider relative advantage

The expected costs for the technology provider are assumed to decrease as the hospital use of identification standards increases over time. This assumption considers the costs of the upgrades and maintenance of the applications associated with identification standards adoption and use.

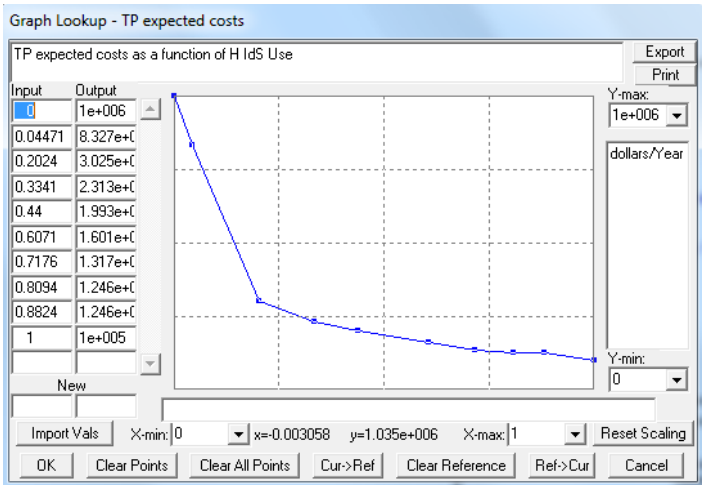

Figure 20. Technology provider expected costs

Complexity and interoperability are considered as a single element in the simulation model to represent the level of commitment of technology solution providers in addressing complexity and interoperability related issues. It is assumed that initially those issues are not addressed by technology providers but as the adoption process moves forward, the issues are solved in order to support adoption. This factor, *complexity and interoperability issues*, was defined as a parameter within the model using a numerical scale to represent low or high effort from the technology provider to solve these issues.

Component 3 - Organization

According to Table 18, the main factors of the organization section within the CLD are the following: organization readiness (P), organization readiness (T) and hospital relative advantage.

Within this component those factors are considered using 3 graphical functions and 7 parameters. The graphical functions represent the hospital relative advantage (*H relative advantage*), the fraction of processes within the hospital using the identifiers (*process fraction*) and the level of improvement due to identification standards adoption and use (*productivity improvement factor*).

The parameters are used to support the formulation of the hospital relative advantage and the organization readiness as it is explained in the following paragraphs.

From the healthcare provider perspective, the relative advantage includes the difference between the gains and the costs associated with the adoption and use of identification standards. For this factor, as the gain increases, the relative advantage also increases. The gain is related to the difference between the benefits and the costs of adopting identification standards.

The benefits are associated with the reduction of process inefficiencies, increased productivity and reduction of errors due to the use of identification standards. The costs are associated with the implementation and maintenance costs incurred when adopting identification standards (CSC, 1996). The benefits and implementation costs are different by process group type but it can be aggregated as shown in Table 20.

The following are the assumptions associated to the cost benefit estimation:

- There are challenges on measuring ROI on health IT related investments (Menachemi & Brooks, 2006). Identification standards adoption builds over already existing infrastructure and the IT investment has been completed, in particular for healthcare providers. The adoption of identification standards would require upgrades to the current infrastructure given the fact that more than 95% of the hospitals have an MMIM in place. The replacement of such an application is not assumed.
- It is assumed that adopting identification standards is beneficial.
- Cost is not as big of an issue for identification standards adoption as it is for EHR adoption, for which large investments in IT solutions have to be budgeted. The cost of the upgrade is assumed.
- The supply chain perspective is considered, in particular, the processes within the MMIS scope.

According to the generic model shown in Table 19, an average healthcare provider is considered in order to define the benefits and the costs in aggregated terms since specific data on benefits and implementation costs by process type was not available. Data from the HIMSS DB 2008 related to the hospital revenue and operating costs as well as the IS Budget allocation proportion

was used to support parameter development. The following parameters were developed in order to formulate the hospital relative advantage (*H relative advantage)*:

- *average H revenue* and *average H operating expenses*, representing the available resources at the healthcare provider level.
- *IS Budget*, representing the proportion of the revenue allocated to information technology related investments.
- *IdS factor*, representing the allocation of the available resources to the identification standards initiative.
- *H SCM operating costs*, representing the costs associated to internal supply chain related processes.
- *H IdS implementation costs*, representing the costs associated to the upgrades to the current technological infrastructure to support identification standards adoption and use.

Table 20. Identification standards costs and benefits

Process Group	Anticipated Outcomes (benefits)	Cost Implementation	Anticipated Outcomes summary
I	Improved fill rates Increased customer satisfaction Increased data accuracy Increased productivity Reduced costs Reduced cycle time Reduced errors Reduced paperwork Reduced product returns Reduced rework	Investment costs Maintenance costs	Effective communication Eliminated paperwork Improved fill rates Improved productivity Increased customer satisfaction Increased data accuracy Increased productivity Increased reliability Lower inventory levels Reduced back orders Reduced costs Reduced cycle time Reduced errors Reduced labor Reduced mis-picks Reduced paperwork Reduced product returns Reduced rework Overall process improvement
II	Improved productivity Increased customer satisfaction Increased data accuracy Increased reliability Lower inventory levels Overall process improvement Reduced back orders Reduced cycle time Reduced labor Reduced mis-picks Reduced paperwork Reduced product returns Reduced rework	Investment costs Maintenance costs	
III	Effective communication Eliminated paperwork Improved productivity Increased customer satisfaction Increased data accuracy Reduced cycle time Reduced product returns	Investment costs Maintenance costs	

Source: EHCR Report 1996

The hospital relative advantage is formulated as a function of the expected gain obtained by the healthcare provider due to identification standards use. This gain is formulated as the difference between the expected benefits and the expected costs.

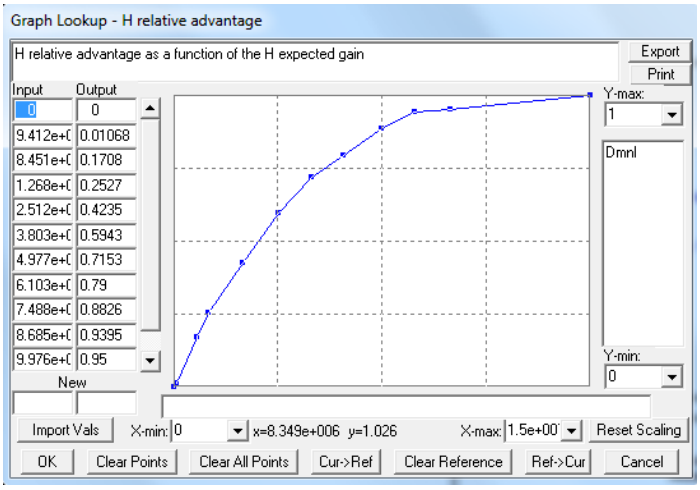

Figure 21. Hospital relative advantage

The expected benefits are formulated as the result of a reduction of the hospital operating costs due to productivity improvements related to identification standards adoption. The expected cost was formulated as the technology implementation costs associated to the upgrades of current supply chain management related applications. The resources are allocated according to the *IdS factor*, which represents the proportion of resources allocated to the identification standards initiative, either via budget or operating expenses. The available resources are the hospital's revenue and operating expenses which values provide an estimate of the hospital size.

The *productivity improvement factor* was defined as an intermediate variable in order to develop the hospital relative advantage formulation. It is defined as the increase in productivity within the healthcare providers supply chain related processes due to the use of identification standards.

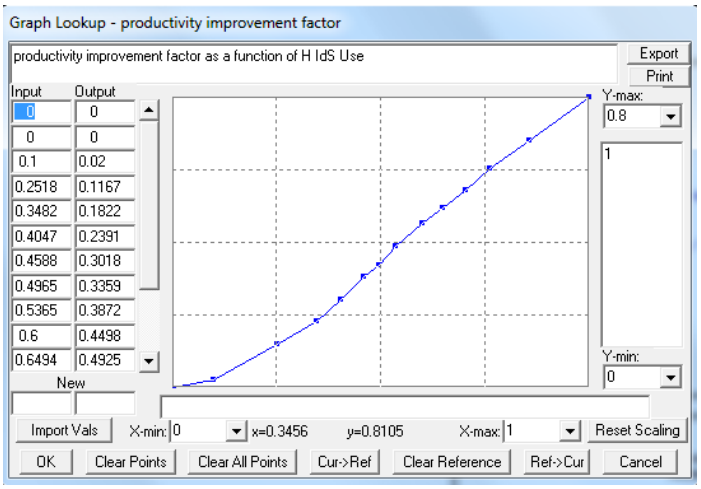

Figure 22. Productivity improvement factor

In general, readiness is defined as the level of preparedness of the healthcare providers towards identification standards adoption. The *organizational readiness (T)* is associated to the technology penetration (supporting technology) and the number of processes using the identifiers. It is assumed that a healthcare provider would be more or less ready, depending primarily upon the penetration of the supporting technology and the internal use of the identifiers. The internal use of the identifiers is formulated as the *organizational readiness (P).*

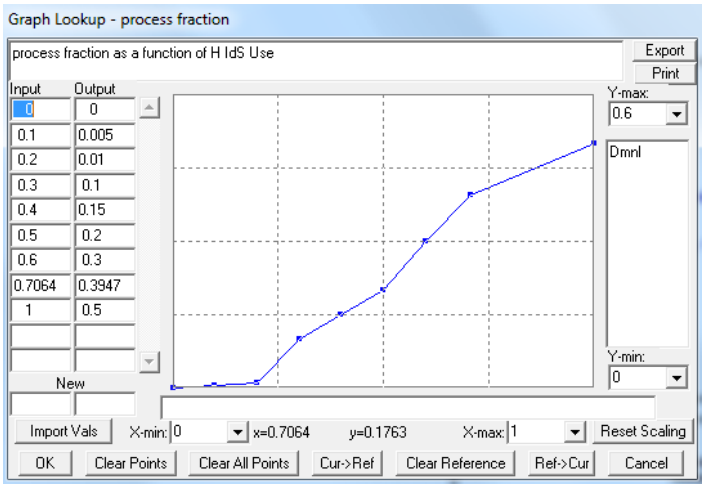

Figure 23. Process fraction

The *organizational readiness (P)* is defined as a function of the *process fraction* which is defined as the fraction of processes within the healthcare provider using the identifiers according to the identification standards definition. This process fraction is assumed to increase over time. The *process fraction* is affected by the *awareness*. The awareness is associated to the number of pilots or industry initiatives that can increase the willingness of the healthcare provider to initiate projects related to identification standards use within internal processes. This parameter is defined on a low to high numerical scale.

Component 4 – Basic population structure

The healthcare provider population is divided among adopters and non-adopters. It is assumed that once a hospital adopts it does not reverse the decision. The adoption rate represents the flow of hospitals from non-adopters to adopters. The basic population structure follows a similar structure as the BDM. The intermediate variable *H IdS Use* is defined as the increase over time on hospital use of identification standards due to the evolution of the hospital population (*adopter influence*).

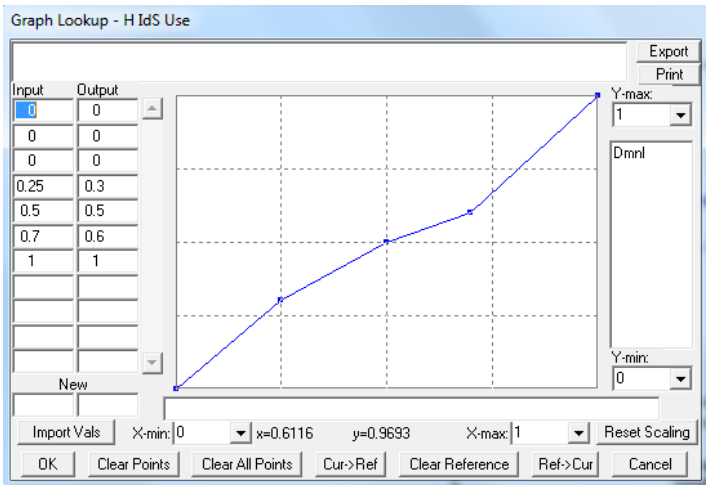

Figure 24. Hospital IdS use

The *H IdS use* variable plays a key role in the integration of Component 3 (C3) and Component 2 (C2) since this variable represents the incremental use of identification standards of the average healthcare provider considered within the generic model. The *productivity improvement factor* and the *process fraction* at the healthcare provider level, and the cost for the technology provider (*TP costs*) are related to this variable.

5.1.3 Generic model structure

As described in the BDM formulation a given population (healthcare provider) is influenced by external and internal factors (Maier, 1998). The external factors are out of their control and not directly related to the healthcare provider population. The internal factors are related directly to the healthcare provider population and are influenced by the adoption of other population members. The model components are related to the internal and external diffusion coefficients in the following way. As shown in Figure 25, Component (C1) is related to the external diffusion coefficient and Components (C2) and (C3) are related to the internal diffusion

coefficient. The main parameters within Component 4 (C4) are the ones related to the population and the initial values of the diffusion coefficients that are to be affected by the formulation of the different factors by component. Those initial values were estimated based on the analysis of the model parameters developed in Stage 1. In the simulation model each component is defined by a set of multipliers which have an effect on the hospital adoption rate. Within each component the average effect of the multipliers is considered. The adoption rate is formulated as the sum of the external and internal influences. The generic model structure is illustrated in Figure 25.

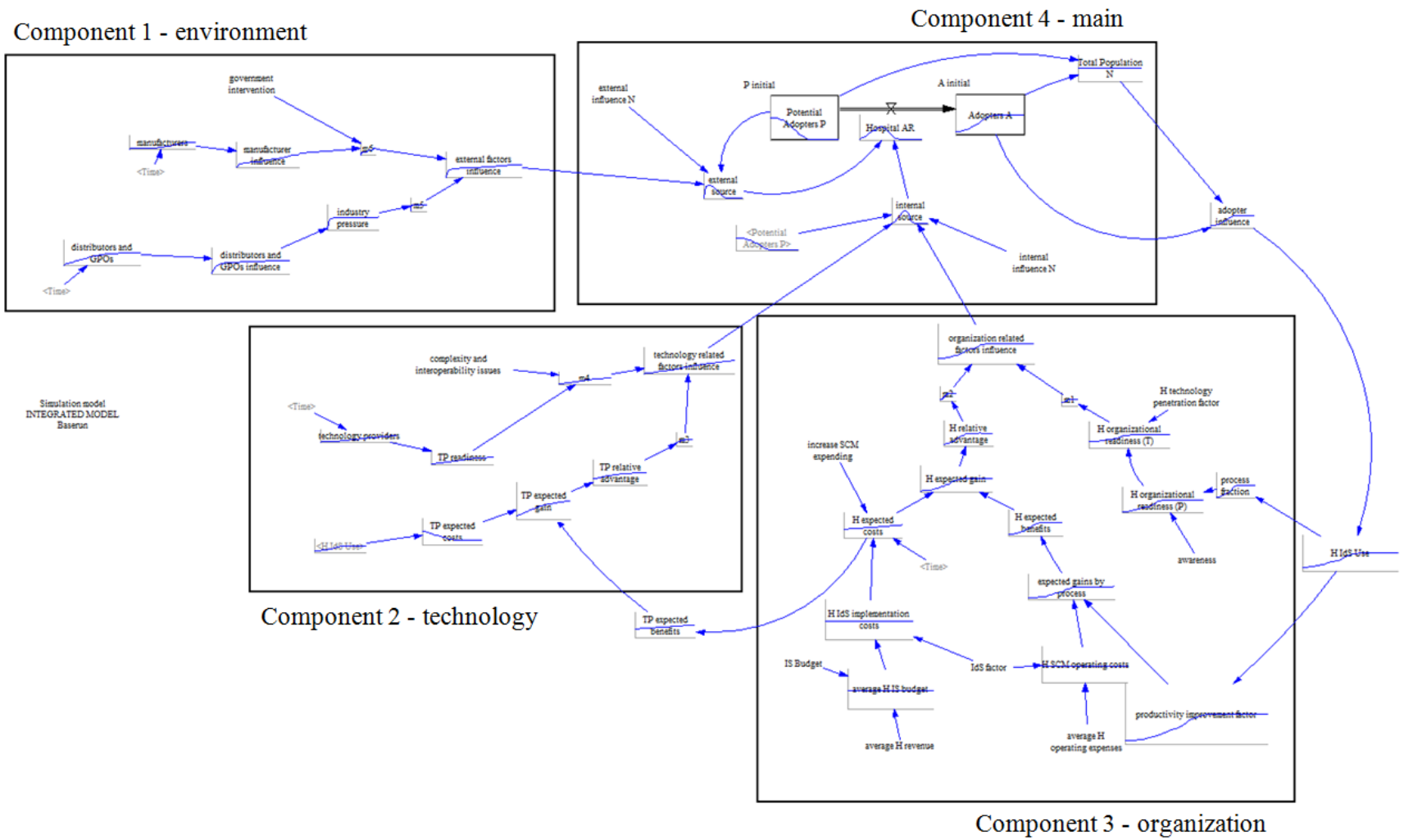

Figure 25. Simulation Model

5.2 Model formulation structure implementation

This section describes the process followed in order to implement the model formulation structure proposed in the previous section. This implementation was performed using the simulation tool Vensim PLE Plus version 5.11A.

5.2.1 Implementation steps

The simulation model was developed by first testing each component (including graphical functions and parameters) individually and then adding one at a time trying to stay close to the reference model pattern. The MMIS adoption pattern developed in Section 4.6 was followed as a reference model. The testing and addition sequence in Vensim started with the organization component (Component 3); this component was added to the basic structure of the simulation model (Component 4) trying to develop a stable model close to the reference model. The same step was followed for Components 2 and 1. The parameters within Component 4 (C4) remained unchanged during the testing and development process.

The graphical functions and parameters listed in Appendix C are part of the final version of the model. During the model development ten integrated test models were developed and tested by comparing the exhibited behavior for the main output variable to the reference model. For example earlier model versions included the integration of Component 4 (C4) with Component 3 (C3), once the fitting to the reference model was achieved another component was added to the test model. A sequential adjustment (testing and development) process was performed until a stable model behavior related to the reference model was obtained. During the testing and development process, different types of adjustments were identified. There were adjustments

related to the range and function shape of the graphical functions, adjustments related to the range of the parameters; and adjustments related to the formulation of each one of the component multipliers. Each one of those changes was addressed component by component until a final integrated model formulation was developed. The model that fitted the reference model more closely was selected as the model baserun. At each step of the model implementation, the model was verified using the Vensim PLE Plus tools: model check and units check in order to identify and correct any errors.

5.2.2 Base run development

One of the main challenges developing the base run was to obtain data to feed the model. For the reference model (Stage 1) it was not difficult to collect and analyze the data directly from the HIMSS DB in order to estimate the model parameters; however, for the model in Stage 2 the parameter estimation was not as straightforward and the only way to obtain reference data for the model base run was to rely on the available sources, such as the HIMSS DB, literature sources, expert's interviews and the researcher's judgment. This approach to parameter estimation is supported by (Glöber, Thun, & Milling, 2008). Some of the parameter definitions of similar models, such as the ones described in (Maier, 1998) and (Erdil & Emerson, 2009), were revised in order to guide the model adjustment. The model base run values were developed in parallel while developing and implementing the model structure.

The model initial conditions consist of a set of conditions that can be grouped in two categories: graphical functions and parameters. The graphical functions guide the behavior of the components and those were described in Section 5.1. The graphical functions are the model assumptions and were used to configure the model parameters. The parameters are classified

into four groups according to their characteristics and numerical values. The first group includes the parameters related to the external forces that affect the adoption rate. The parameters that are related to the availability of resources at the healthcare provider level are included in group two. The third group of parameters includes those related to values that control the allocation of resources as well as the technology availability. The last group includes the parameters directly related to the composition of the healthcare population. The classification of the parameters and the base run values are presented in Table 21.

Table 21. Model baserun

group	parameter	IM Baserun initial
1	governmentintervention	1
	complexity and interoperabilityissues	1
	awareness	1
2	average H operating expenses	262,364,000
	average H revenue	270,826,000
	IS Budget	0.03
3	H technologypenetration factor	0.4
	IdS factor	0.05
	increase SCM expending	0.01
4	A initial	500
	externalinfluence N	0.02
	internalinfluence N	0.32
	P initial	2500

The complete model formulation is presented in Appendix C.

5.2.3 Validation

Validation can be viewed as a process of establishing confidence in both the behavior and the structure of a model (Finkelstein, Homer, & Sondik, 1984). The validation process was

performed using the base run values defined in the previous section and considering the assumptions contained in the graphical functions. The model was tested under the following validation tests (Sterman, 2000):

- Behavior reproduction
- Dimensional consistency
- Parameter assessment
- Sensitivity analysis (See section 5.3)

Behavior reproduction

The model's main output was compared with one or more historical data series available for similar adoption processes. In this particular case the MMIS reference model is followed. It was also useful to compare the different patterns obtained under different input assumptions with diffusion patterns of similar technologies. The model was able to produce outputs that corresponded to past historical trends (Stage 1 reference model), and the results were within a reasonable range.

Dimensional consistency

The model was tested for dimensional consistency by using the Vensim model check and units check options. The model was verified for consistency at each step of the implementation process, and the corresponding adjustments were made until consistency was achieved and no errors were reported.

Parameter assessment

The different model components were used to test each one of the parameters within the component. The components were used as submodels to test the consistency and also to partially test and adjust the parameters. The parameter assessment was followed at each step of the model implementation process, and the adjustments to the model parameters were made until a stable model behavior was achieved.

5.2.4 Simulation results (base run)

The numerical results of the output of the simulation are presented in Table 22. The model was run over a period of 40 years, with the year 2008 as the initial year. This starting year was selected since it was the year that the main initiative related to identification standards adoption started (DeJohn, 2008).

Table 22. Simulation baserun results

	Baserun	results
Main input	Y0	2008
	Horizon	40
	N	3000
	A0	500
	P	2500
	p	0.02
	q	0.32
Main output	Years to AR peak	14
	Inf. Point (year)	2022
	AR max (H/year)	185
	Critical mass (H)	2014
	Saturation point (year)	2038
	End year	2048

Although different starting dates could have been analyzed, thereby shifting the year the adoption rate would reach its maximum level, in general the span of the adoption process and the number of healthcare providers required for the inflection point (critical mass) would be the same. The results from running the model under the assumed initial conditions, gives a 14 year period for the adoption rate to peak or reach its inflection point which is estimated at about 2014 hospitals (critical mass).

The main behavior output measures of the model are the behavior of the adoption rate and the behavior of the adopter population. The behavior patterns of the main outputs of the simulation model are presented in Figure 26.

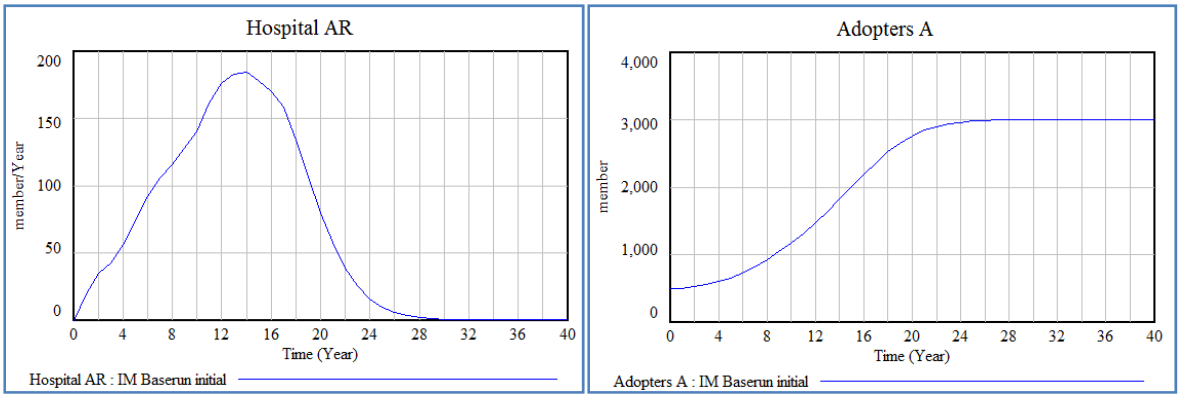

Figure 26. Simulation base run results (output measures)

Behavior of the Adoption rate AR

One of the measures of the adoption rate behavior is the time to peak (Hekimoglu & Barlas, 2010). The behavior of the adoption rate is illustrated in Figure 26a. The time of peak is year 14, which represents the highest point of the adoption rate at 185 healthcare providers per year.

The adoption rate of 185 at its peak would mean that the adoption at the healthcare provider level would have to perform at a faster pace. This adoption rate is equivalent to 6.17% (adopters per year/total population), which seems high compared to the 2% reported by (DeJohn, 2008).

Behavior of the Adopter population A

One of the measures of the behavior of the adopter population is the inflection point along with the time to reach equilibrium (Hekimoglu & Barlas, 2010). The inflection point occurs at the peak of the adoption rate, which is year 2022, as shown in Figure 26b. At this point the critical mass of the adopter population has enough inertia to continue the adoption process, and the equilibrium level is reached after the limit of the adopter population is reached. This behavior implies that it would take about 2014 healthcare providers (critical mass) to reach the inflection point.

Using the BDM as the underlying model to describe the identification standards adoption process impose that the external diffusion coefficient is low compared to the internal diffusion coefficient. This means that in the identification standards adoption model most adoptions occur through internal adoptions. The behavior of the hospital population is crucial to drive adoption. This observation is supported by (Fibich & Gibori, 2010). The authors provide an explanation on how the diffusion process develops according to the ratio between the diffusion coefficients p/q. If the ratio is less than one, most adoptions occur through external adoption. When the ratio is greater than one, most adoptions occur through internal adoptions. In this case of the identification standards adoption model, the ratio is greater than one (0.32/0.02) which means that most adoptions occur through internal adoptions or factors related to the healthcare provider population.

Under the given baseline, the projected timeline for identification standards adoption is 29 years with a peak at year 14. This information can provide an assessment for the proposed industry deadline of December 2012 for product identifiers. By comparing the timeline given by the model, it can be inferred that the deadline is not going to be met.

Even though no data on past adoptions was found, the literature review provides an indication of the current situation regarding identification standards adoption. According to (DeJohn, 2008) the penetration of identification standards in 2008 was about 2%. A report by (O'Daffer, Shaffer, & Lefebure, 2011) provided an estimate of 625 members joining the identification standards initiative in 2011 but it did not provide an estimate by supply chain member category. The survey by (Pohl & Nachtmann, 2011) shows an increasing participation of all healthcare supply chain members in the identification standards initiative in particular for location identifiers. The use of such identifiers among healthcare providers grew from 10% in 2010 to 22% in 2011. The use of product identifiers was reported as 5% in 2011 mainly by large healthcare providers. The GS1 readiness reports posted in the GS1 website (GS1, 2012) provide an estimate of the number of healthcare providers committed to the identification standards initiative which in 2011 was 745 healthcare providers able to transact using a location identifier in a purchase order via EDI.

The analysis of the previous facts indicates that there is a trend in the evolution of identification standards reported use. The current trend can be compared to the baserun output (See Appendix E). The current trend results are similar compared to the trend indicated by the baserun which gives an estimated timeline of 14 years. These findings provide an indication about the adoption pattern for identification standards and highlight the importance of understanding the factors that

could drive the change and accelerate the process. The sensitivity analysis developed on the next section provides an indication of those factors.

5.3 Model analysis

Sensitivity analysis is important to establish the parameters to which the model output is sensitive; this could lead to improvements in the model formulation, increased data collection efforts and definition of policies to change the model behavior pattern (Ford & Flynn, 2005). This section presents a review on the different methods used for sensitivity analysis of system dynamic models and explains the proposed approach for the sensitivity analysis of the identification standards adoption model (Stage 2).

5.3.1 Sensitivity analysis and SD models

A preliminary step in developing policies is the identification of high leverage parameters and structures which determine the influential model components that could drive the system behavior. There are different methods for sensitivity analysis of system dynamic models, among the most important ones (Hekimoglu & Barlas, 2010) are:

- One at a time approach
- Multivariate approach
    - Statistical screening
    - Behavior pattern analysis
    - Taguchi methods (Design of experiments)

One at a time approach

The variation of one parameter at a time is the most commonly used sensitivity analysis method (Erdil & Emerson, 2009), (Nelson, 1998). It is performed by selecting a critical set of parameters and identifying an output measure. Then by varying each parameter, one at a time, the changes on the output measure are observed. Critical issues are identified, but the analysis is limited because just one parameter is allowed to vary and the other parameters remain fixed.

Statistical screening

Statistical screening (Ford & Flynn, 2005) allows for the identification of high leverage model parameters for further analysis and policy development. Statistical screening is developed in six steps as described below:

1. Select a specific set of model parameters and a performance measure (output variable). Define the range, the percentage of variation and the distribution function for the model parameters.
2. Perform statistical screening of the model to calculate the correlation coefficients. Plot the correlation coefficients and the behavior of the performance measure for all simulations in another graph.
3. Select a time period for analysis by examining the time series of the correlation coefficients and the performance measure behavior.
4. Identify high influence parameter(s) during the selected period as those with the highest magnitude of correlation coefficient values.

5. Identify high level model structures (components) as those that are directly driven by the high influence parameter(s) identified in the previous step.
6. Use additional structure-behavior analysis methods to explain how the high leverage model structures identified in step 5 which drive behavior.

High leverage parameters identified by the use of statistical screening can be used to design policies. However, a better use of statistical screening is to exploit the results to identify the link between the identified parameters and specific model structures that can be further analyzed, decomposed or expanded in order to improve the model validity. That information can also be used to improve the understanding of how the model structure drives behavior and how potential extensions improve model validity and policy testing (Ford & Flynn, 2005).

Behavior pattern sensitivity

Behavior pattern sensibility is focused on examining the effect that changing the value of defined model inputs could have in the output patterns of the model (Hekimoglu & Barlas, 2010).

As with most of the sensitivity analysis methods, the selection of the model parameters to be analyzed and the distribution function for each one must be defined. Then a sampling strategy must be selected (e.g random sampling or Latin Hypercube Sampling) in order to run the model and collect the data related to the output pattern. A multiple regression model can be used to estimate the regression coefficients and to establish the relationships between the selected parameters and the output measure. One of the limitations of this approach relies on the assumption of the linear relationship between the output measure and the regression coefficients.

Taguchi methods

According to (Clemson, Tang, Pyne, & Unal, 1995) Taguchi methods provide a more systematic way to conduct experimentation for sensitivity analysis purposes, but it would require the estimation of a single measure as the output of the simulation model. The authors compare Taguchi methods and Latin Hypercube Sampling (LHS). For a full factorial approach a ten parameter model with 3 levels would require 3^{10} trials (59,047). The LHS scheme ensures that all regions for the sample space are represented. LHS combines many of the advantages of simple random sampling and full factorial designs but requires far fewer trials. As an alternative, Taguchi methods of experimental design could provide a more efficient way to conduct the experiment. In this case, the ten parameter model with three levels can be studied with 27 trials using a Taguchi L_{27} orthogonal array.

5.3.2 Model analysis – evaluation of different approaches

After the review of different methods, it was observed that for most models the sensitivity analysis was performed by varying parameters one at a time. The one at a time approach would not be useful for the model developed in this chapter because it was assumed that there are different parameters interacting.

Taguchi and regression models used in behavior pattern sensitivity analysis methods would require the estimation of a single output measure as a result of each simulation run. In the case of the present model, the estimation of a quantitative value related to the total output of the simulation is not feasible (or would not prove useful), since the goal of the model is not to estimate a total output but to describe an adoption pattern.

For the sensitivity analysis of the present model, a combination of statistical screening (Ford & Flynn, 2005) and behavior pattern sensitivity (Hekimoglu & Barlas, 2010) is proposed. The statistical screening facilitates the analysis of the behavior over time of an output variable due to changes in a given set of parameters. The analysis is performed via the estimation of the correlation coefficient between a given parameter and the output variable at each step of the simulation (Ford & Flynn, 2005). The Correlation Coefficient (CC) ranges from -1 to +1 and illustrates the strength of the relationship between two variables without accounting for other variables that could be influential. The formula of the correlation coefficient is:

$$r = \frac{\sum(X_I - \bar{X})(Y_I - \bar{Y})}{\sqrt{\sum(X_I - \bar{X})^2 \sum(Y_I - \bar{Y})^2}} \qquad (20)$$

For example, if a model is run for a period of 10 years and there are 3 parameters and 1 output variable, the correlation coefficient for each parameter with the output variable would need to be estimated for each one of the time periods.

The steps proposed by the statistical screening method (Ford & Flynn, 2005) are followed and complemented by the definition of the model output measures as behavior patterns. As explained by (Hekimoglu & Barlas, 2010), the behavior patterns of model variables are more important than their numerical values. In the specific case of this research, the identification standards simulation model exhibits an S-shaped growth for the adopter population; in this case the exact value of the variable at a specific time is not as important as it is the inflection point, the equilibrium level or the time to equilibrium. This is the reason why the behavior pattern of the *adopter* population is considered as one of the main output measures of the model for

sensitivity analysis purposes along with the behavior of the *adoption rate.* These are the two main output variables of the model although the adoption rate will be used more frequently.

5.3.3 Sensitivity Analysis

The model was initially analyzed with the support of the SyntheSim Vensim functionality in order to observe the behavior of the main output variables. This functionality allows for the researcher to test the model with considerable interactivity. The changes made to the model while in this mode will cause the model to be re-run automatically (Ventana, 2007). The parameters defined in the baserun were tested for sensitivity by parameter group. The parameters listed by group and the corresponding values are presented in Table 23.

Table 23. Sensitivity analysis parameters

	parameter	IM Baserun	Low	High	distribution
1	government intervention	1	1	3	RANDOM_UNIFORM
	complexity and interoperability issues	1	1	3	RANDOM_UNIFORM
	awareness	1	1	3	RANDOM_UNIFORM
2	average H operating expenses	262364000	174909333	349818667	RANDOM_UNIFORM
	average H revenue	270826000	180550667	361101333	RANDOM_UNIFORM
	IS Budget	0.03	0.02	0.04	RANDOM_UNIFORM
3	H technology penetration factor	0.4	0.24	0.56	RANDOM_UNIFORM
	IdS factor	0.05	0.03	0.07	RANDOM_UNIFORM
	increase SCM expending	0.01	0.006	0.014	RANDOM_UNIFORM
4	A initial	500	400	600	RANDOM_UNIFORM
	P initial	2500	2000	3000	RANDOM_UNIFORM

The parameters within group one are related to external forces influencing each of the main model components. These forces are out of the control of the healthcare provider. Under current conditions those parameters are set to one. The parameters within group two are related to the availability of resources. The parameters within group three are related to the allocation of the

resources and technology infrastructure. The parameters within group four are related to the population size.

A period of 30 years was defined as the horizon to run the model sensitivity analysis tests. For each parameter group a sensitivity analysis test was performed leaving the parameters within the other groups unchanged. Four tests were performed:

- Test 1, sensitivity analysis test for parameters within group 1, remaining parameters were kept unchanged.
- Test 2, sensitivity analysis test for parameters within group 2, remaining parameters were kept unchanged.
- Test 3, sensitivity analysis test for parameters within group 3, remaining parameters were kept unchanged.
- Test 4, sensitivity analysis test for parameters within group 4, remaining parameters were kept unchanged.

The following steps were followed to perform each sensitivity analysis test:

1. Define the range, variation and distribution function for the parameters under analysis.
2. Load parameters into the Vensim PLE Plus sensitivity analysis module.
3. Select the sampling strategy (LHS) and the number of runs (50 runs).
4. Run sensitivity analysis for each output measure (behavior patterns) and save the data.
5. Export data to MSO Excel and develop correlation coefficient (CC) plots according to the template provided by (Ford & Flynn, 2005).

6. Analyze. The period of analysis for the adoption rate pattern was defined as the period before the adoption rate peak. This period was used because the goal is to establish the main parameters influencing the adoption rate and the identification of main model components of greater leverage in order to speed up the adoption process. For the sensitivity analysis of the adopter population, the complete span of the simulation was considered.

The Vensim sensitivity analysis reporting functionality offers the option of displaying sensitivity analysis graphs as the ones shown in Figure 27. For example Figure 27 shows the sensibility analysis graph for the adoption rate which includes the results of the simulation runs in the form of confidence bounds; the 50% region includes all the runs that felt within that range. This illustration provides an indication of the variation of the output variable regarding the parameters associated with a given sensitivity analysis test.

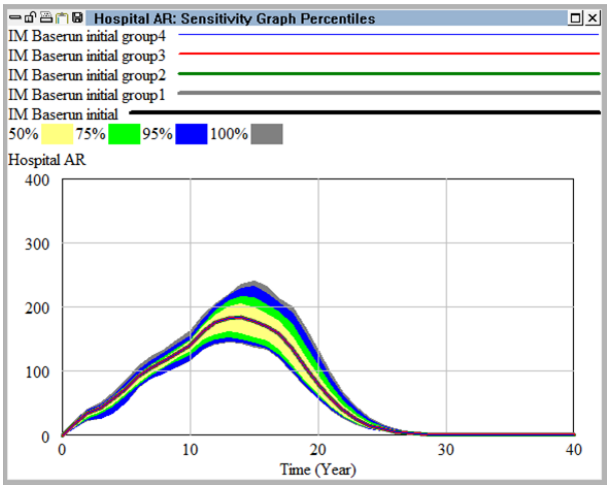

Figure 27. Sensitivity analysis results (Vensim graph)

After exporting the Vensim sensitivity analysis results to MSO Excel, the main parameters were identified by analyzing the threshold range (Ford & Flynn, 2005) for the Correlation Coefficient (CC) plots which is (+0.2, -0.2). The parameters that fall outside of the threshold range are considered to have an impact in the output measure under analysis.

After analyzing the results of the sensitivity analysis (CC plots) for the adoption rate behavior pattern and the adopter population pattern, it was found that the relevant parameters within each test are the same for both output measures. This can be explained by reviewing the discrete version of the BDM (See Equation 5) in which the adoption rate is formulated as a function of the cumulative number of adopters.

Within test 1, the result of the analysis of the CC plots shows that *complexity and interoperability issues* is a relevant parameter. Within test 2, the analysis of the CC plots shows that the *IS Budget* and the *Average H revenue* are relevant parameters. Within test 3, the analysis of the CC plots shows that the *IdS factor* is a relevant parameter. Within test 4, the analysis of the CC plots confirmed what is already known about the impact of this type of parameters. The analysis showed that the *P initial* parameter has an increasing correlation and the *A initial* parameter has a decreasing correlation; these results were expected as they confirmed what is already known about the impact of these type of parameters (Ford & Flynn, 2005). For the main component (C4), changes related to the parameters can have an impact on the adoption rate however those changes are not considered for sensitivity analysis purposes since only one population size is considered in the simulation model.

After reviewing the results of the tests, a fifth test (test 5) that includes the combination of the parameters within groups 1, 2 and 3 is proposed. The analysis of the results of test 5 indicated

that the following factors have a correlation with the adoption rate: *IdS factor, average H operating expenses, complexity and interoperability issues* and *awareness.* For group one parameters such as the *awareness* and the *complexity and interoperability issues* at the healthcare provider and the technology provider level respectively, can play a role in facilitating identification standards adoption. For parameters within groups 2 and 3, these results indicate that the availability and allocation of resources at the healthcare provider level considering that the *average H operating expenses* and the *IdS factor* may have an impact on the adoption process. The results for the sensitivity analysis are summarized in Table 24.

Table 24. Sensitivity analysis results

group	Relevant parameters test 5
1	government intervention
	complexity and interoperability issues
	awareness
2	***average H operating expenses***
	average H revenue
	IS Budget
3	H technology penetration factor
	IdS factor
	increase SCM expending

As the underlying BDM formulation suggests, the internal adoption influence is stronger than external influence. An analysis of the relevant parameters by component shows that for Component 1 (C1) the parameter *government intervention* did not appear on any of the aspects of the analysis as a relevant parameter, so the contribution of Component 1 (C1) is low. For Component 2 (C2) the parameter *complexity and interoperability issues* appear as a relevant parameter, which indicates that actions directed to solve those types of issues could have an impact in the adoption rate. For Component 3 (C3), there are three parameters that can play a

role on speeding the adoption process; those are *awareness*, *average H operating expenses* and *the IdS factor*. The analysis by group indicates that parameters associated to the healthcare provider can be important when considering the design of the interventions. The result of the Correlation Coefficient CC plot for test 5 is shown in Figure 28.

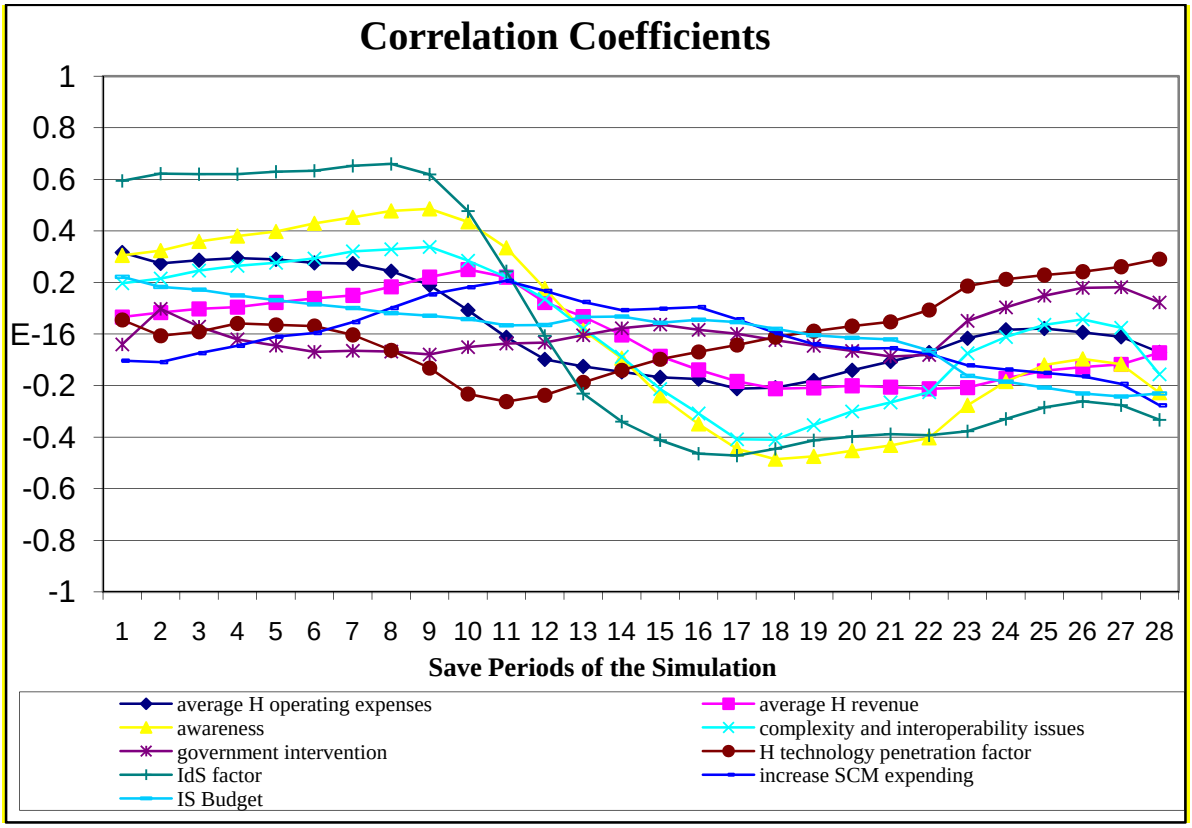

Figure 28. Correlation coefficient plot (test 5)

The threshold range of (-0.2,+0.2) illustrates how the parameters that fall outside of the threshold are the ones included in the analysis as relevant parameters and are highlighted in bold in Table 24. The complete report of the sensitivity analysis tests including both output measures is presented in Appendix D.

The results of the sensitivity analysis provide an indication of the relevant model parameters. It also provides information related to the model behavior and how the model can be improved. The improvements can lead to the evaluation of data collection efforts and the definition of policies to change the model behavior pattern. Based on this information, an interpretation of those results in the context of real world can be developed but the interpretation will be limited by the assumptions and scope of the model. The model does not attempt to make a prediction of what is going to happen in the future but to provide a test bed for interventions testing.

5.4 Model interventions (design and implementation)

This section presents the answer to the following research question:

What actions are required to increase the number of healthcare supply chain members and healthcare providers adopting identification standards?

The answer to this research question is presented under the scope of the model defined and analyzed in this chapter. The model includes the hospital population, but other members besides the technology providers were not explicitly considered due to the limitations on data availability. A literature review regarding policy design interventions development for system dynamics models in the form of policy design or scenario testing is presented, and then the proposed interventions for the present model are developed.

5.4.1 Review

For system dynamics models, the interventions or changes in the system are usually introduced in the form of policies or scenarios.

Policy design

The adoption of Electronic Health Records (EHR) modeled by (Erdil & Emerson, 2009), using a system dynamics model, presented 4 policies. These policies were related to the cost, which was identified as one of the main factors affecting the EHR adoption. The policies included the addition of subsections to the original model in order to reflect the policy intervention in the form of subsidies, free grant products, a tax break and paying for performance. The model developed by (Otto & Simon, 2009) on EHR adoption, illustrated how policies can be defined as a set of changes on parameter values. The policies were defined as a 20% variation on the selected parameters (financial incentives, awareness and education) to show the impact in the adopter population.

Scenario testing

The adoption of technologies in agricultural business was studied by (Fisher, Norvell, Sonka, & Nelson, 2000), and the scenarios tested different combinations of profit levels to observe the impact on the speed of diffusion. The adoption of food safety technologies was studied by (Daim, Rueda, Martin, & Gerdsri, 2006), and the scenarios were used to establish the most likely set of parameters that could explain the adoption process within a reasonable timeframe. The scenarios developed by (Cui, Zhao, & Ravichandran, 2011) for the new product launch allowed researchers to test a combination of launch strategies and market size in order to evaluate the speed of diffusion of a new product.

5.4.2 Interventions within the present research model

Intervention design

For the present model the interventions are defined as a set of policies and scenarios. The interventions are designed based on the following sources: the sensibility analysis results from the previous section and a set of future events.

The results from the sensitivity analysis emphasize the importance of the organization related Component (C3) and suggest that the external Component (C1) is not so relevant. The fact that the Component 1 (C1) is not relevant can be understood under the BDM model structure assumption since the external diffusion coefficient is small and it drives that portion of the adoption process which has a small impact in the adoption rate. As for Component 2 (C2), the *complexity and interoperability issues* parameter was found as a relevant one. As for Component 3 (C3), the *IdS Factor* and the *average H operating expenses* were relevant parameters which are associated with the resource allocation and availability. Also for this component the *awareness* was found as a relevant parameter which is directly linked to the *organizational readiness* factor. Policies and scenarios that include these model parameters could have an impact in the main output measure (Hospital adoption rate).

There are a set of future events that could have an impact in the current model. The design of the interventions considered the following: the impact of the FDA UDI regulation, the impact of the enforcement of the minimum use requirements for hospital EHR implementation and the impact of the increased participation of the technology providers in the identification standards adoption

process. These events were identified through the extensive literature review developed in Chapters 2 and 3.

Intervention evaluation

The model allows for the testing responsiveness of the main variable such as the hospital adoption rate to the proposed interventions. The impact of the intervention (policy or scenario) is measured as the shift of the adoption rate curve relative to the baseline (adoption rate peak), the adoption rate (adopters per year at the peak) increase, and the critical mass change.

5.4.3 Interventions by component (design and implementation)

Based on the sensitivity analysis results and the events related to a given model component a set of policies for each component is proposed.

Component 1

As revealed by the sensitivity analysis of the parameters within group 1 and the combined analysis (test 5), none of the parameters within Component 1 (C1) were relevant. The different factors defined within the external environment could have an impact in the adoption rate. The values that those parameters represent are the current status of the system if no other change is introduced.

Assuming that the UDI regulation could take place at the end of 2012, the model would consider that the regulation has an effect at the manufacturer level. The model takes into consideration the members of a given population; it does not consider the granular effect of products flowing through the system. Under the current model the number of manufacturers joining the initiative

is considered. The model assumed a parallel development from the manufacturer side on the deployment of barcode labels for all product classes.

The configuration of the model by product would require distinguishing among the three product classes. Such a model could provide an estimation of the evolution of the number of product identifiers over time but not of the use of product identifiers within the processes and transactions at the healthcare provider level, as the current model does. The immediate pressure for UDI adoption would be for manufacturers of products Class III. Products Class III are the ones that could represent a potential risk to the patient, while products Class I represent no harm (Hefflin, 2005). It is estimated by the industry that it would take about two years for manufacturers of products Class III to fully comply with the regulation. It could take five years or more for manufacturers of products Class I to fully comply with the FDA regulation. Even if the product came with barcodes from the manufacturer to the hospital, the technology, processes and procedures required to make use of those identifiers would have to be in place. This means that, even if the UDI rule effect is immediate, and product identifiers are available tomorrow on all products in the form of the GTIN minimum level of AIDC marking (GS1 Healthcare US, 2010), which does not consider secondary information, it will take hospitals as long as it took them to adopt the underlying technological infrastructure, to use identification standards within the described processes under the identification standards definition.

As shown in Figure 25, Component 1 (C1) is linked to the adoption rate via the external diffusion coefficient. For policy 1a, a change in this structure is proposed in the form of a single coefficient. Policy 1a was defined as a change in the model structure to illustrate the impact of the consolidation of the internal and external diffusion coefficients into a single one. The impact

of this change is significant given the fact that the adoption rate peak gets delayed to year 20 when the Component 1 (C1) effect is considered jointly.

Policy 1b is defined as a change in the *manufacturers* function (gf), representing one third of the population members adopting by year 15 and a STEP function for the *government intervention* parameter with a height of 5 and a step of 2. The details of policy development are shown in Appendix E. This policy shifts the adoption rate peak from year 14 to year 11. The result of the implementation of both policies is shown in Figure 29.

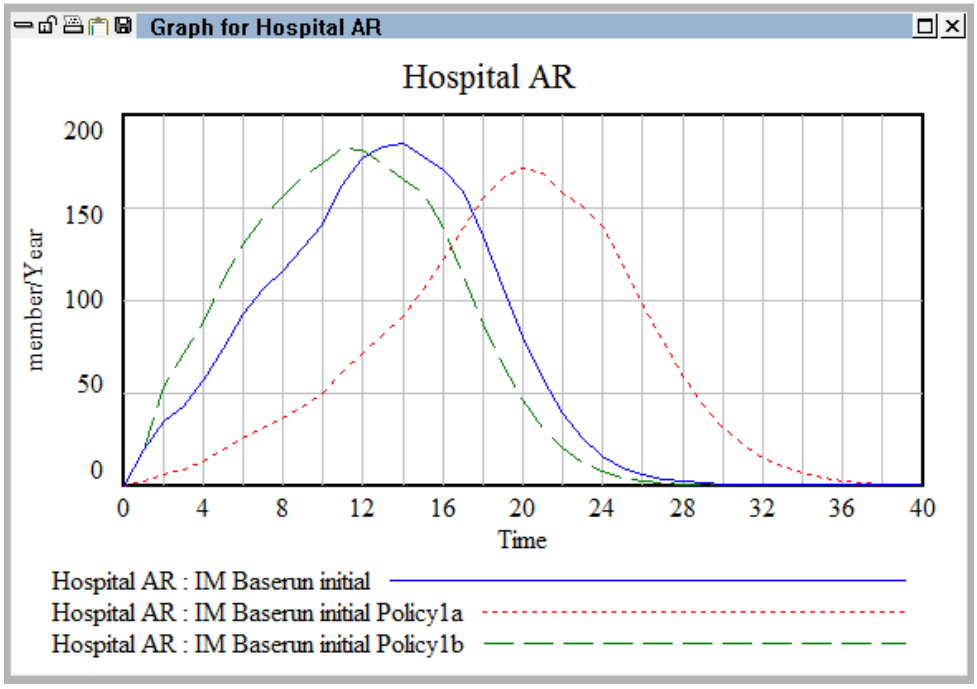

Figure 29. Policies Component 1 (C1)

In the context of the real world the implementation of Policy 1b indicates that increasing the number of manufacturers joining the initiative as well as introducing an intervention by the government could help to shift the adoption rate curve to the left. This policy can be associated to the effect of the UDI FDA rule over manufacturers.

Component 2

The technology provider plays a role in identification standards adoption by facilitating the upgrades required for the supporting technology currently in place at the healthcare provider level. The *complexity and interoperability issues* parameter appears as a relevant one in the sensitivity analysis; this means that changes in this factor could have an impact on the adoption rate. The policies related to the technology provider can be aimed to increase the technology provider readiness (*TP readiness)* in order to solve *complexity and interoperability issues* associated to identification standards adoption. The results of the policy implementation are shown in Figure 30.

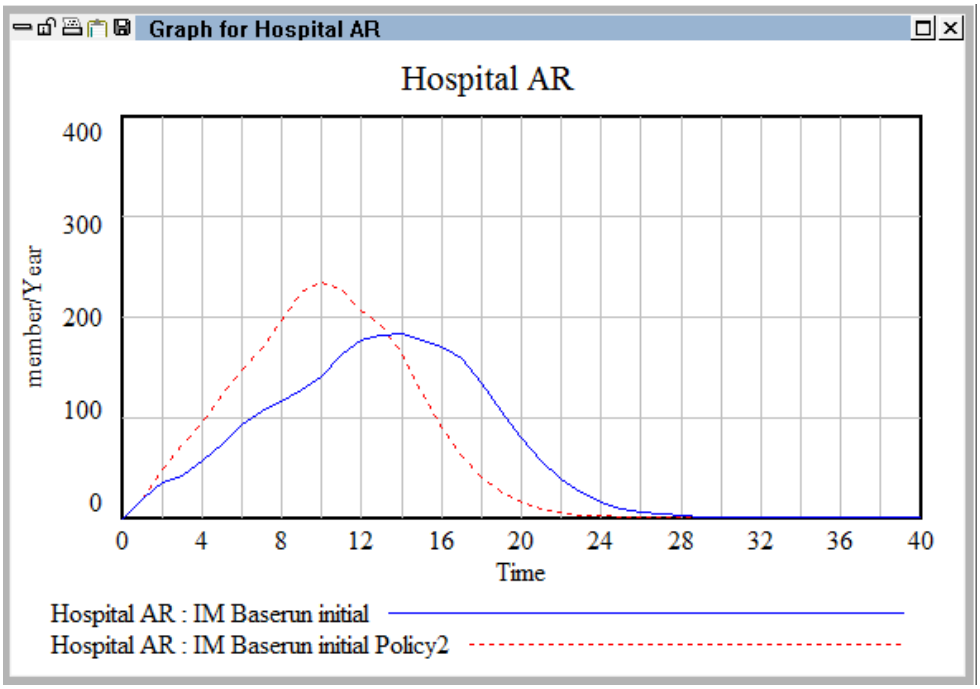

Figure 30. Policy Component 2 (C2)

Policy 2 was defined as a change in the technology provider readiness to illustrate the impact that the number of technology providers joining the initiative could have on the adoption process. It

was assumed that one third of the technology providers were joining the initiative by year 10. The details of policy development are shown in Appendix E. It can be observed that the adoption rate peak shifted from year 14 to year 10 and the number of healthcare providers per year (at the peak) also increased from 184 to 234.

In the context of the real world the implementation of Policy 2 represents a shift of the adoption rate curve to the left due to the increased involvement of the technology providers in the identification standards initiative.

Component 3

According to the results from the sensitivity analysis, *awareness* is a relevant parameter in the model, as well as *IdS Factor* and *average H operating expenses*, which means that changes in those parameters could have an impact in the adoption rate. An increase in the *awareness* would represent an increase in the healthcare provider readiness. An increase in the *IdS Factor* would represent the fact that more resources are allocated to the identification standards initiative. Changes in resource availability are not included in this policy since the *average H operating expenses* factor which is linked to the resource availability, thus the size, is associated in the present model to one population size (H>2).

Although the *H technology penetration factor* did not show a significant impact, it can play a role in identification standards adoption. The model takes into consideration only the supporting infrastructure from the supply chain perspective but other technological components have to be integrated, especially as the product flows through different units within the hospital and are used at the point of care. Additionally, the presence of EHR minimum use requirements in the

form of financial incentives could represent a way to drive the adoption. An increase in the *H technology penetration factor* is proposed as a way to represent the required technological integration to meet the EHR minimum use requirements and its associated incentives.

For Policy 3, it is assumed that in order to increase the healthcare provider readiness, the event of an increase in the level of technological integration can be represented by a value of 0.8 for the *H technology penetration factor* and an increase in the *awareness* can be represented by a value of 3 for this parameter. The *IdS factor* is set to 0.06 to represent an increase in the resource allocation and the *average H operating expenses* was kept unchanged. The implementation of this policy gives a shift of the adoption rate peak from year 14 to year 9.

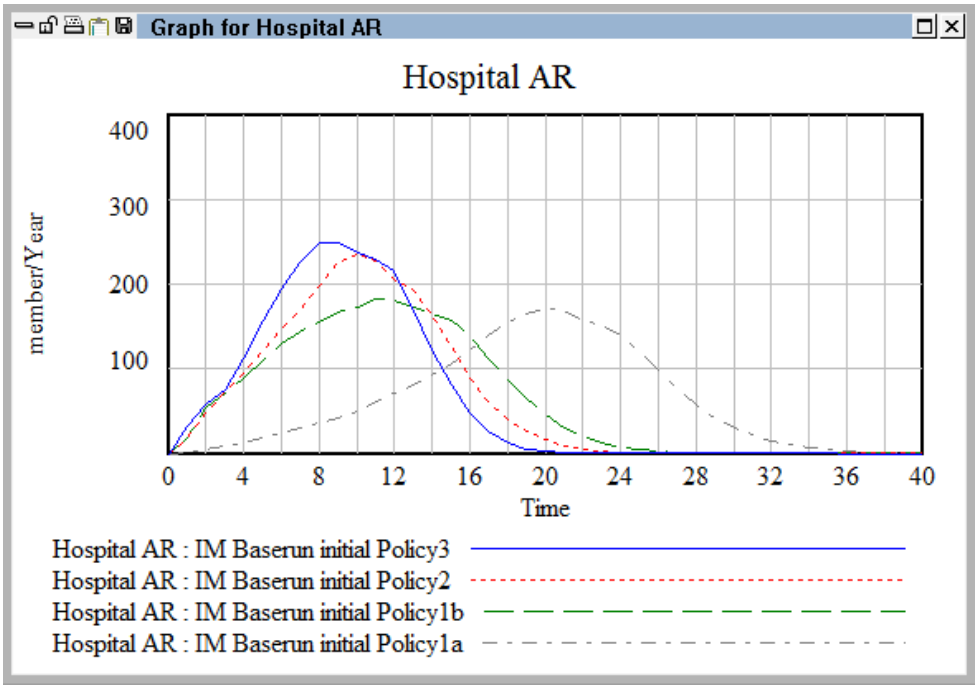

Figure 31. Policy Component 3 (C3)

In the context of the real world the implementation of Policy 3 represents the effect of an increase in the healthcare provider readiness due to an increase in the awareness which can be

associated to an increased number of pilots of the early adopters. The implementation of the policy explores an increase in the healthcare provider technological integration due to the implementation of EHR minimum use requirements. This policy also includes an increase in resource allocation which could represent the fact that more resources are allocated to upgrade the existing applications to meet the identification standards requirements.

A summary of the policies is presented in Table 25. Among the different policies, the one that provides the earliest adoption rate peak (year 9) is Policy 3. This policy directly affects Component 3 (C3) and reflects an increase healthcare provider readiness via an increase in the awareness regarding the identification standards initiative. This policy also included an increase in the *H technology penetration factor* due to the EHR minimum requirement implementation pressure and an increase in resource allocation due to the increase of the *IdS factor*.

Table 25. Policy implementation summary

Policy (Vensim model)	Description	AR max	Year peak	Critical mass	End year
IM Baserun initial	Inital conditions	184	14	2014	29
IM Baserun initial Policy1a	Single diffusion coefficient	171	20	1892	38
IM Baserun initial Policy1b	Government intervention and increased number of manufacturers	182	11	1793	28
IM Baserun initial Policy2	Increased number of technology providers	234	10	1831	26
IM Baserun initial Policy3	Technological integration, awareness and increased resources	248	9	1851	21

Given the fact that each policy represents an effect on a single component, the combination of different policies is proposed as a way to explore the impact of such interventions in the model.

Four policy combinations are proposed as shown in Table 26. The first policy combination includes the parameter changes proposed for Policy 1b and Policy 2. This policy combination represents an increase in government intervention and also an increase in the number of manufacturers and technology providers joining the identification standards initiative. The second policy combination includes the parameters changes proposed for Policy 2 and Policy 3. This policy combination represents an increase in the number of technology providers joining the identification standards initiative as well as an increase in the readiness at the healthcare provider level.

Table 26. Policy combinations

Policy combination	Description
(1) Policy 1b and Policy 2	Government intervention and increased number of technology providers joining the initiative
(2) Policy 2 and Policy 3	Increased number of technology providers joining the initiative and increased technological integration at the healthcare provider level as well as an increase in the awareness and resources
(3) Policy 3 and Policy 1b	Government intervention and increased technological integration at the healthcare provider level as well as an increase in the awareness and resources
(4) Combined policy	Participation of all stakeholders

The third policy combination includes the parameter changes proposed for Policy 3 and Policy 1b. This policy combination represents efforts by the healthcare provider regarding the identification standards initiative as well as an increase in government intervention and the number of manufacturers joining the identification standards initiative. The last combination is the combined policy which includes the main parameters within each policy. This policy combination represents the joined effort of all the stakeholders. For this combined policy the *government intervention* parameter is set at 3, *complexity and interoperability issues* parameter is

set at 2, *awareness* parameter is set at 3, the *hospital technology penetration factor* is set at 0.6 and the *IdS factor* is set at 0.07. As proposed by (Glöber, Thun, & Milling, 2008) the values for the different parameter changes can be supported by information gathered through literature sources, sensitivity analysis testing and the researcher's experience.

The result of the implementation policy combinations is shown in Table 27. The policy combinations that provide the earliest adoption rate peak are policy combination (2) and (4). By analyzing the information provided in Table 27, it can be observed that the interventions that are associated with Policy 3 provide a better performance regarding the adoption rate peak as well as the duration of the adoption process.

Table 27. Policy combinations results

Policy combinations (Vensim model)	AR max	Year peak	Critical mass	End year
(1) IM Baserun initial Policy1b and 2	242	9	1871	24
(2) IM Baserun initial Policy2 and 3	353	7	2007	17
(3) IM Baserun initial Policy3 and 1b	263	8	1799	21
(4) IM Baserun initial combined policy	352	7	1819	16

The Vensim graph for the policy combinations is shown in Figure 32. The implementation of policy combinations (2) and (4) generate an adoption rate peak at year 7.

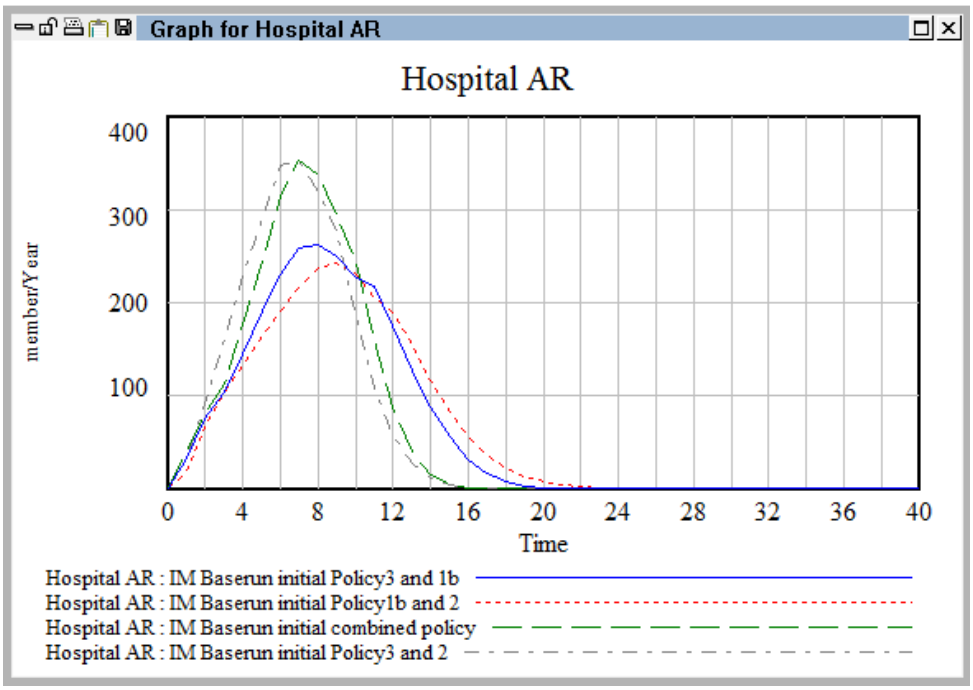

Figure 32. Policy combinations graphical output Vensim

The results of the implementation of the proposed policies contribute to the understanding of the system behavior and provide an indication about the impact of the proposed changes in the system. The information that supports policy analysis and development is presented in Appendix E.

5.4.4 Interventions by scenario definition

The scenario definition is determined by the combination of the main parameters identified in the sensitivity analysis and their corresponding levels. The parameters are *complexity and interoperability issues*, *awareness*, *average H operating expenses* and *IdS factor*. The levels were defined within the range of the numerical scale previously assigned to the parameter. Three levels were defined for each parameter: High, Medium and Low. The parameters and the levels are shown in Table 28.

Table 28. Parameters and levels for scenario analysis

Parameter	label	Level		
		1	2	3
complexity and interoperability issues	A	1	2	3
awareness	B	1	5	10
average H operating expenses	C	174,909,333	262,364,000	349,818,666
IdS factor	D	0.03	0.05	0.07

In order to test the different combinations of model parameters, the basic structure of an orthogonal array was defined (Clemson, Tang, Pyne, & Unal, 1995). In this case the orthogonal array represents a matrix that ensures a balanced comparison of levels of any parameter (factor). A L_9 (3^4) experiment for 9 tests, 4 factors and 3 levels was used. There are nine scenarios according to the L_9 (3^4) experiment template as shown in Table 29.

The scenarios were tested in Vensim PLE Plus, and the output of the simulations were saved and analyzed in MSO Excel. There were two experimental results that were not considered within the analysis because the lack of stability of the results (Scenarios 8 and 9).

Table 29. Scenarios

Scenarios	A	B	C	D
1	1	1	174,909,333	0.03
2	1	5	262,364,000	0.05
3	1	10	349,818,667	0.07
4	2	1	262,364,000	0.07
5	2	5	349,818,667	0.03
6	2	10	174,909,333	0.05
7	3	1	349,818,667	0.05
8	3	5	174,909,333	0.07
9	3	10	262,364,000	0.03

The results are summarized in Table 30. There are two scenarios that show an adoption rate peak at year 7; those are scenario 4 and scenario 7.

Table 30. Scenario results

Scenarios (Vensim model)	AR max	Year peak	Critical mass	End year
IM Baserun initial	184	14	2014	29
IM Baserun initial scenario1	143	21	1800	30
IM Baserun initial scenario2	230	12	2009	23
IM Baserun initial scenario3	334	8	1900	17
IM Baserun initial scenario4	326	7	1667	18
IM Baserun initial scenario5	376	15	2043	22
IM Baserun initial scenario6	403	8	2025	14
IM Baserun initial scenario7	368	7	1819	17

For scenario 4 the *complexity and interoperability issues* are partially solved. The allocation and availability of resources is high according to the values of the *IdS factor* and the *average H operating expenses*; the level of *awareness* is low. For scenario 7 the *complexity and interoperability issues* are fully addressed, and the resource allocation and availability is also high; the level of awareness is low.

By analyzing the characteristics of these scenarios an indication of the possible effective interventions can be established. The participation of the technology provider in order to solve complexity and interoperability issues as well as the allocation and availability of resources at the healthcare provider level are observed as important interventions to consider. The analysis by policy did not include a change in the parameter associated with the availability of resources; in the scenario testing this factor appears high as well as the resource allocation factor. The allocation of resources is associated to the fact that financial resources can be provided to the

identification standards initiative within the healthcare provider. The availability of resources is associated with the size; so it seems that hospitals with more resources, could adopt faster.

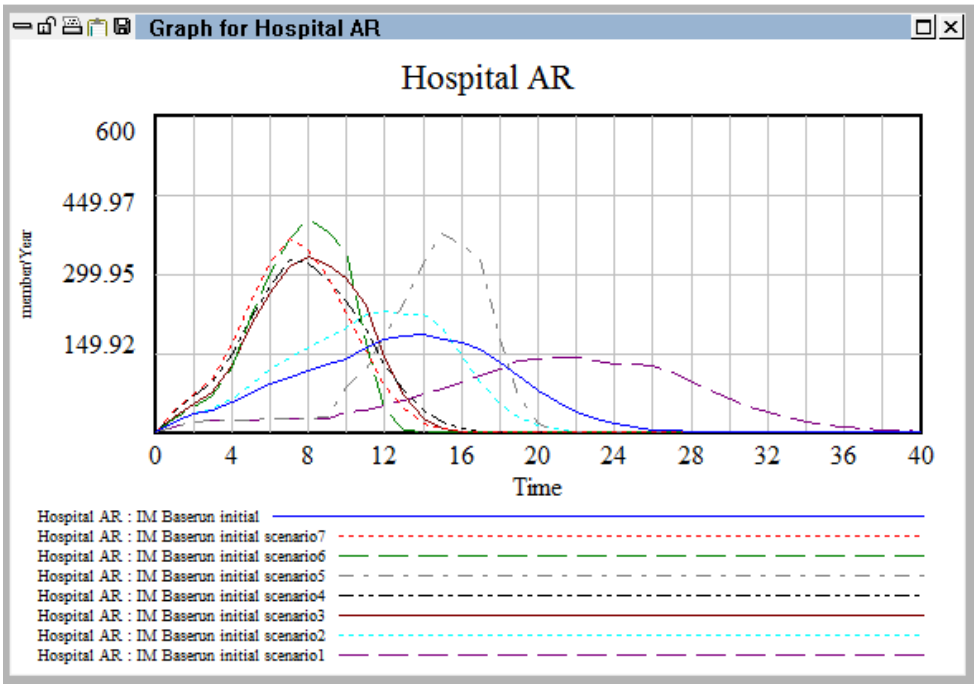

Figure 33. Scenarios Vensim output

The Vensim graph of the scenario testing is shown in Figure 33. By comparing the parameters included within Scenario 4 and Scenario 7, it can be observed that the most likely scenario is the one that includes actions associated to solve complexity and interoperability issues as well as an increase in resource availability and allocation at the healthcare provider level. The information that supports scenario analysis and development is presented in Appendix E.

5.5 Conclusions

This chapter presented the second stage of the modeling approach to identification standards adoption. The proposed model is an answer to research question number 4. In this regard, the

challenges posed by the use of classical diffusion models which were discussed in the previous chapter were addressed. The proposed model developed in this chapter is an answer to those challenges. The model uses the information configured in the model parameters and graphical functions to show the current status of the system and to project the adoption pattern of identification standards diffusion over time. Under the initial conditions it would take 14 years for identification standards adoption to reach its peak and 29 years to complete the adoption process. The model results are limited to the available information and model assumptions but it provides a way to assess current industry deadlines for identification standards adoption and provides an answer to the problem described in Chapter 1. As explained in Section 4.5.3 the goal of the model is not to forecast but to provide an explanation of the current situation and to understand the system behavior.

Within this modeling stage, the answer to research question number 5 is developed. The answer to this question is incorporated within the formulation of the main elements of Component 3 (C3) (See section 5.1.2). It is assumed that the adoption of identification is beneficial for the healthcare provider and the productivity improvements will represent a gain for the healthcare provider. Since ROI data was not available the justification of identification standards benefits or the estimation of the ROI is out of the scope of this research

The sensitivity analysis of the model allowed for the identification of the factors affecting the identification standards adoption process; it also facilitated the understanding of the system behavior and allowed for the design and test of interventions to move the system forward. Among the relevant parameters are the ones associated with Component 3. Since the baserun

results indicate that the industry deadline of December 2012 is not going to be met, the sensitivity analysis results provide information to guide interventions design.

Finally, the model analysis presented in this chapter contributes to answer the research question number 6. The question is related to the required interventions to increase the number of healthcare providers adopting identification standards. The proposed interventions were designed in accordance to the results from the sensitivity analysis and the most likely future events. Two types of interventions were considered: policies and scenarios.

Among the different policies, when analyzed independently the ones that act directly over Component 3 (C3) are the most effective, producing an adoption rate peak at year 9. The implementation of policy combinations (2) and (4) produce an adoption rate peak at year 7 as well as implementation of Scenarios 4 and 7.

Given the results of the implementation of the proposed interventions, the adoption (adoption rate peak) of identification standards can be shifted to year 7 if the conditions proposed by the policy combinations (2) or (4) or the Scenarios 4 or 7 are assumed.

The policy combinations associated to the earliest adoption rate peak are characterized by efforts at the healthcare provider level. Policy combination (2) included a joined effort from technology providers as well as healthcare providers; similarly policy combination (4) included a joined effort of all stakeholders.

The scenarios associated to the earliest adoption rate peak (Scenarios 4 and 7), are characterized by a low level of awareness and high level of resource allocation and availability at the

healthcare provider level. The participation of the technology providers in order to solve complexity and interoperability issues is also a characteristic of these scenarios.

This model provides an illustration of the use of system dynamics models and diffusion theory to understand a problem reported in the literature and not yet solved. This model is an approximation of the real world system that allows the identification of the main factors affecting the system and facilitates the design and testing of policies to explore the change in the system behavior. This approximation is proposed as a way to understand the problem and shed light to real world practitioners and also to the academic community on issues like the lack of data and other challenging aspects of empirical research which can be addressed with the proposed model and methodology.

6. Conclusions

6.1 Contributions

The contributions from this research are related to each one of the expected contributions presented in Chapter 1.

The contributions from Phase I are associated with the classification of the major barriers affecting the identification standards adoption process. The literature review related to technology adoption and diffusion within the healthcare domain was developed, and the adoption of Electronic Health Records (EHR) was identified as one of the main adoption processes within that category. The literature review related to the technology adoption and diffusion outside the healthcare domain was developed, and the adoption of Electronic Data Interchange (EDI) was identified as one of the main adoption processes within that category. The results of the literature review on identification standards literature illustrated the lack of academic literature related to identification standards adoption and supported the need for a conceptual model to explain it.

The researcher developed a conceptual model that is an original contribution to the literature. The classification of the factors identified through the extensive literature review provided the basis for the development of the conceptual model for identification standards adoption. The conceptual model illustrates the factors affecting the adoption of identification standards from the healthcare provider perspective (Burbano, Rardin, & Pohl, Exploring the Factors Affecting the Identification Standards Adoption Process, 2011). Those are categorized as environment, technology and organization related factors.

The technology related factors are relative advantage, complexity, compatibility and the organizational readiness factor in terms of the technological capabilities. These factors are directly associated with the characteristics of the technology (innovation) under study and the preparedness of the organization related to its infrastructure to support the adoption. The relative advantage represents the benefit associated with the technology, and it is used instead of the cost in order to express the gain from technology adoption in aggregate terms. The environment related factors are industry pressure, government intervention, vendor support and the technology solution provider readiness factor in terms of its ability to support the technology to be adopted by the healthcare provider. These factors are outside of the control of the healthcare provider. The organization related factors are size, top management support, and organizational readiness factor. These factors are directly related to key characteristics of the organization (e.g size) and also to basic elements of the project and team required to lead the adoption process.

The contributions from Phase II are associated with the development and implementation of the proposed modeling approach for identification standards adoption. This research makes a first attempt to model identification standards adoption by bringing system dynamics modeling and diffusion theory together. The proposed model provides insights on relevant factors affecting the adoption process and illustrates how policies and scenarios are designed to modify the system's behavior.

The initial step of the proposed modeling approach is the Causal Loop Diagram (CLD). This CLD is another representation of the factors affecting the adoption process, identified in the conceptual model, but in the form of a relationship (Burbano, Pohl, & Rardin, Modeling the Adoption of Identification Standards in US Hospitals: A Systems Dynamics Approach, 2011).

The CLD was used to conceptualize the model formulation. The use of classical diffusion models was explored as a way to mathematically formulate the model, and the Bass Diffusion Model (BDM) was proposed as the underlying structure for the formulation. Due to the lack of information on past adoptions related to identification standards, a staged model formulation was proposed.

The first stage of the model formulation used the BDM to analyze the adoption of the technology required to support identification standards use. It was assumed that the analysis of the adoption of supporting technologies for identification standards such as the MMIS could provide valuable information to model the identification standards adoption process, since identification standards cannot be used in isolation but require the existence of an underlying platform to be of any value for the organization. This stage facilitated the estimation of the model coefficients for each of the supporting technologies, according to the identification standards definition. It also facilitated the characterization of the diffusion curves for MMIS, BPOC and EDI for the hospital population using the HIMSS DB available data.

The second stage of the model used most of the factors defined in the CLD to develop a simulation model, which was validated using the steps suggested by the system dynamics methodology. The sensitivity analysis identified the relevant model parameters that facilitated the design of interventions to move the adoption process forward. This model provides an illustration of the use of system dynamics models and diffusion theory to understand a problem reported in the literature and not yet solved. This model is an approximation of the real world system that identified the main factors the system and facilitated the design and testing of policies to explore the change in the system behavior. This approximation is proposed as a way

to understand the problem and inform real world practitioners and also the academic community on issues like the lack of data and other challenging aspects of empirical research that can be addressed with the proposed model and methodology.

6.2 In general (research questions, limitations and challenges)

As presented in Chapter 1, the research questions were grouped into two phases. Phase I was related to questions 1, 2 and 3. Phase II was related to questions 4, 5 and 6. For each phase the main objective was achieved and the research questions were answered.

For Phase I the main objective was to identify the main barriers affecting the data standards adoption process (research question number 3). The barriers were identified and the adoption process was explained via a conceptual model. The research shows that the identification standards adoption process can be understood and explained using the information provided in the comparative analysis of findings and the proposed conceptual model. The findings of Phase I are limited to the scope of the literature review, which was extensive and covered more than 100 papers, but it cannot be assumed that all the available documentation was revised.

For Phase II the main objective was to develop a theoretical model to investigate the dynamics of the adoption of identification standards in the U.S healthcare supply chain (research question number 4). The model was developed and tested. A systems dynamics modeling approach was used to model this process, and the model was based on technology diffusion theory. The research showed that technology diffusion models can be used to explain and model the adoption of identification standards, but with certain limitations. Classic diffusion models such as the BDM are limited to data availability and the definition of the technology to be adopted.

To overcome those limitations, a two stage formulation was proposed. The first stage comprised the modeling of identification standards supporting technologies, such as MMIS, BPOC and EDI, by using the BDM. It was established that the adoption of at least the underlying platform, the MMIS, was necessary to support identification standards adoption and further use. The second stage comprised the model formulation, implementation and testing using the assumptions developed in Section 5.1.

According to the results of the sensitivity analysis the following factors were found to have a positive correlation with the adoption rate: *IdS factor*, *average Hospital operating expenses*, *complexity and interoperability issues* and *awareness.* These results indicate that the availability and allocation of resources at the healthcare provider level considering the *average H operating expenses* and the *IdS factor* may have an impact on the adoption process. The implementation of the interventions defined in Section 5.4 indicated that the adoption rate for identification standards can be accelerated up to year 7.

The model (Stage 2) allowed the researcher to model interactions and facilitated the development of assumptions when no data exists or is available yet. The model provides a platform or test bed that can be extended to include other healthcare supply chain stakeholders. Even though there are different stakeholders in the healthcare supply chain, this model's main focus is the healthcare provider and its interaction with technology providers. The findings from this phase are limited to the validity of the model parameters and assumptions.

The development of the first phase was challenging due to the lack of a consensus on identification standards adoption definition. An operational definition was proposed. The development of the second phase of the research was challenging due to the fact that classical

diffusion models rely on the existence of enough data on past adoptions in order to estimate model parameters. Since identification standards were defined as a recent adoption process (2008), the lack of data on past adoptions represented a challenge for modeling purposes. The staged formulation was proposed as a way to overcome this challenge.

6.3 Research opportunities

Some of the challenges described in the previous section represent an opportunity for further research and exploration.

The study of the identification standards adoption process from the Management of Technology (MOT) perspective provided an opportunity to enhance the understanding of the adoption process by exploring related adoption processes such as EDI and EHR. That exploration led to the development of the conceptual model for identification standards adoption at the healthcare provider level. The extension of this work in order to develop a conceptual model for other healthcare supply chain members such as distributors, Group Purchasing Organizations GPOs and manufacturers could be considered. These conceptual models can be tested ona broader scale with a data collection technique (survey). A longitudinal study can be developed based on the operationalization of the conceptual model (survey results). This study can be done over a three to five year period to collect data on adoption and follow up on the industry evolution.

The simulation model (Stage 2) can be improved with the refinement of the data gathering and validation process. The use of fuzzy set theory in order to operationalize the qualitative variables of the model is an avenue for future exploration.

The generic simulation model structure can be further developed to include the specific characteristics of the healthcare population (size, revenue) and also to consider other industries for example the pharmaceutical supply chain.

The methodology used to develop the simulation model can be revised, and Agent Based Modeling ABM can be applied to study individual entities instead of a population. These entities can be modeled as individual hospitals, and spatial considerations associated with geographical characteristics can be considered as well as network membership.

In general, the proposed modeling approach of Stage 2 and the groundwork information provided in Stage 1 can be followed and improved in the study of adoption processes with similar characteristics in a different setting, for example a different country.

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Appendix A. Literature review supporting information

A.1 Adoption determinants related literature (part A)

Grover	Nelson	Ramamurthy et al	Iacovou et al	Palmer
1993	2003	1995	1995	1998
Organizational factors	Technology	Organizational factors	Organizational readiness	Organizational
Centralization	Relative advantage	Management support	Financial resources	Size
Integration	Compatibility	Task scope	Technological resources	Ownership
Size	Complexity	IS sophistication		Vertical integration
IS related Support factors	Cost	Championing	Perceived benefits	
	Organizational		Actual direct Indirect benefits	
IOS Factors	Champion	Organization learning		
Compatibility	Top management support	Elapsed t (adoption)	External pressure	Technological
Relative advantage			Competitive pressure	IS staff size
Complexity	IS organization		Imposition by partners	In house development
	Infrastructure			IT investment
Environmental factors	Strategic planning	Innovation factors		Centralization
Industry related		Compatibility		
Customer related	External environment	Complexity	EDI Adoption	
	Competitive pressure	Cost effectiveness	EDI Integration	Strategic
	Market	Relative		
Policy factors	uncertainty	advantage	EDI impact	Strategy
Environmental interaction	Power			Early adoption
Competitive strategy	Trust			
Risk position				

A.2 Adoption determinants related literature (part B)

McGowan and Madey a	Kuan et al	Narayanan et al	Chang et al
1998	2001	2009	2007
<u>Organization</u> Size Management support Champion Technical expertise Training Centralization Functional differentiation External communications <u>Innovation</u> Compatibility Complexity Relative advantage <u>Environment</u> Customer influence Supplier influence Industry cooperation Vendor support	<u>Organization</u> Financial cost Technical competence <u>Technology</u> Direct benefits Indirect benefits <u>Environment</u> Industry pressure Government pressure	Adoption determinants External factors Internal factors Firm operations Anticipated benefits Supplier-buyer relationships EDI integration Internal integration External integration Realized outcomes	<u>Organizational characteristics</u> User involvement Adequate resources Hospital size Internal need <u>Technology characteristics</u> Security protection System complexity <u>Environment characteristics</u> Vendor support Government policy

Appendix B. Parameter estimation

B.1 Tool

Angelica Burbano

From: Arvind Rangaswamy [axr15@smeal.psu.edu]
Sent: Tuesday, April 12, 2011 12:08 PM
To: Angelica Burbano
Cc: Gary Lilien; 'Mike Clitherow'
Subject: Re: question

Angelica,

The software is available at http://www.mktgeng.com/diffusionbook/. Please check to make sure that you have the correct operating system and Excel version to run the software. The other option is to purchase the latest version of our Marketing Engineering software -- I have copied Mike Clitherow, whom you can contact for further information regarding the latest version of the software.

Arvind Rangaswamy

On 4/12/2011 12:58 PM, Angelica Burbano wrote:
Dr. Rangaswamy, I am a graduate student at the University of Arkansas.
I would like to know if I could have access to the MS Excel tool referenced in the chapter you co-authored with Dr. Lilien and Van Den Bulte "Diffusion Models: Managerial Applications and Software".
I got the book through a library loan system from the University of Kansas Library but the disk does not contain any files.
I appreciate your collaboration.
Regards,
Angelica

Ps. I also wrote to Dr. Lilien

Angelica Burbano
Graduate Research Assistant
Center for Innovation in Healthcare Logistics
University of Arkansas
4123 Bell Engineering Center
Office (479) 575 2300
Fayetteville, AR 72701

Figure B.1.1 Software request

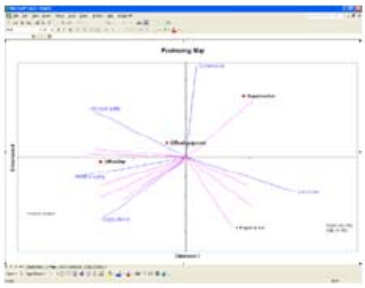
DecisionPro, Inc

Marketing Engineering

Computer Assisted Marketing Analysis and Planning

Search

ME Home >> New-Product Diffusion Models book



New-Product Diffusion Models book

Introduction

The following Bass model software is designed to accompany the book New-Product Diffusion Models by Vijay Mahajan (Editor), Eitan Muller (Editor), and Yoram Wind (Editor). This download will give a limited time license to the Bass Model software which is part of the Marketing Engineering for Excel software package by DecisionPro. For more information on Marketing Engineering for Excel, please visit www.DecisionPro.biz for commercial applications or browse this website for academic use.

Software Requirements

Operating System:
- Windows 2000, XP, or Vista

Additional Software Requirements:
- Microsoft Office 2002 (XP), 2003, or 2007
- Adobe Reader 6.0 or higher (for access to the tutorials)
- Microsoft .NET 2.0 Framework

Download

File Name: MEXL_BASS_032808_installer.exe
Version: 1.2
Date Published: March 28, 2008
Download Size: 35.9 MB

download

(Note: If you have trouble downloading the .EXE version of this software, please download the ZIP'd version.)

Installation Instructions

For more detailed instructions, please view the Getting Started Guide.

1. Be sure Microsoft Excel is closed.
2. Download MEXL_BASS_032808_installer.exe installation package and save to desktop.
3. Double-click MEXL_BASS_032808_installer.exe file to start installation. Installation may take several minutes depending on speed of your machine.
   - If you do not have Microsoft's .NET 2.0 Framework installed, installation will warn and abort. Download .NET 2.0 Framework and double-click file to install.
   - Repeat Step 3.

Figure B.1.2 Software access page

B.2 Available information

Usage Agreement and Application for the Dorenfest Institute for H.I.T. Research and Education Database

1. The Database

The Dorenfest Institute for H.I.T. Research and Education Database includes a variety of detailed historical data about information technology (IT) use in hospitals and integrated delivery networks. This data includes the entire library of Dorenfest 3000+Databases™ and Dorenfest Integrated Healthcare Delivery System Databases™ for the period 1986 through 2003 (hereinafter referred to at the 'Database'), and 2004 through 2008 data from the HIMSS Analytics™ database.

Access to and use of this Database at no charge is restricted to universities, students under university license, and U.S. federal, state, and local governments, and governments of other countries that will be using the data for research purposes. Potential users ('Licensees') to this Database must read this Usage Agreement and complete and submit the Application for Access to The Dorenfest Institute for H.I.T. Research and Education Database included within this Usage Agreement.

The Database will be available to the Licensee via a secured Web site.

2. Term of License

Authorized Licensees will receive access to the Database for a period of six (6) months from the time the application is approved.

3. Nature of License

- The Licensee acknowledges and agrees that: (i) the Licensed Data is proprietary to and the confidential property of the Licensor and constitutes valuable information in which the Licensor holds all trade secret rights and copyrights; (ii) the Licensee acquires no right(s) in the Licensed Data except to use the Licensed Data solely within the Licensee's own organization or agency and for the Licensee's own purposes during the License Term in accordance with this Agreement; and (iii) the Licensee and its affiliates will not challenge the rights claimed by the Licensor in the Database and the Licensed Data. The Licensee agrees to treat the Licensed Data in the same manner as the Licensee's most confidential information, but in any event not less than a reasonable degree of care.
- The Licensee will take appropriate measures, by instruction, agreement, or otherwise, to ensure compliance with this Agreement during his or her relationship with the Licensee and thereafter pursuant to this Agreement. Unless the Licensee has obtained the express prior written authorization of the Licensor, the Licensee shall not use all or any part(s) of the Licensed Data for numerical or text quotation(s) for advertising or public relations. The Licensee shall not copy or reproduce in any form any or all of the Licensed Data unless the use of that data is related to the research project described in the Licensee's Usage Agreement and Application for Access to The Dorenfest Institute for H.I.T. Research and Education Database. However, under no circumstances can the Licensee reproduce the Database in its entirety.
- The Licensee agrees to cite the source of the data used from The Dorenfest Institute for H.I.T. Research and Education Database. The following language must appear at the bottom of each page in an article or research paper in which the data is cited:

Data Source: The Dorenfest Institute for H.I.T. Research and Education, HIMSS Foundation, Chicago, Illinois, 2010.

- The Licensee agrees to keep the unique password provided to the Database private and not share it with individuals not covered in the Application.
- The Licensee agrees to submit the written results of the research project (e.g., white paper, research report, thesis, article) to The Dorenfest Institute within 30 (thirty) days after the conclusion of the research project. The Licensor will have the right to post the report, article, or thesis on the Dorenfest Web site, as part of the Dorenfest database, unless the Licensee has submitted the document for publication in a professional journal, magazine or book.
- The Licensee should indicate whether the report, thesis, article, etc. will be submitted for publication.
- Notwithstanding the above, the Licensee shall have no obligations with respect to any information in or about the Licensed Data demonstrated to have already been known to the Licensee before receipt of the Licensed Data, or otherwise is or becomes part of the public domain without violation of this Agreement.

4. Warranty

The Licensee acknowledges that the data in the Database are collected by or on behalf of the Licensor and, while the Licensor reasonably believes such data to be accurate, the Licensor makes and Licensee receives no warranty, express or implied, and all warranties of merchantability and fitness for a particular purpose are expressly excluded. The Licensor shall have no liability with respect to any or all of its duties and obligations under this agreement for consequential, exemplary, special, or incidental damages, even if the Licensor has been advised of the possibility of such damages. In no event shall the Licensor's liability for damages, regardless of the form of action, exceed the amount paid by the licensee for the relevant licensed data.

5. Termination

Whenever the Licensor has knowledge or reason to believe that the Licensee has failed to observe any of the terms and conditions of this Agreement, the Licensor shall notify the Licensee in writing of the suspected breach. If, within 30 days of such notice, the Licensee fails to prove to the Licensor's reasonable satisfaction that the Licensee has not breached this Agreement, the Licensor may terminate the License and this Agreement.

6. Other

- The Licensee may not assign or sub-license to any person or entity its rights, duties, or obligations under this Agreement, to any person or entity, in whole or in part. This Agreement is binding upon the Parties and their respective heirs, assigns, and successors in interest.
- This Agreement and performance hereunder shall be governed by the laws of the State of Illinois without reference to conflicts of laws provisions.
- Notwithstanding anything to the contrary in this Agreement, the Licensee acknowledges and agrees that the Licensor in its sole discretion may change any or all of the format and content of the database at any time.

Figure B.2.1 HIMSS Dorenfest Data Base agreement

Angelica Burbano

From: foundation@himss.org
Sent: Thursday, November 18, 2010 5:58 PM
To: aburbano@uark.edu
Subject: You now have access to the Dorenfest Institute

Dear Angelica Burbano,

You have been granted access to the The Dorenfest Institute for Health Information Technology Research and Education.
You will be able to access the databases from 11/18/2010 until 5/18/2011.

This on-line tool can be accessed by visiting: http://www.himss.org/DorenfestInstitute/Login.aspx
User Name: aburbano2
Password: joe092

Questions should be forwarded to 312-915-9523 or foundation@himss.org.

Figure B.2.2 Access to the Dorenfest Institute

B.2.3 List of available information

Library of Dorenfest 3000+ Databases™ and Dorenfest Integrated Healthcare Delivery System Databases™ for the period 1986 through 2006
http://www.himss.org/DorenfestInstitute/DatabaseListing.aspx
Last access 4/14/2011 4:58 PM

2008 HIMSS Analytics Database (derived from the Dorenfest IHDS+ Database) (Access 2003)

- Demographic and IT data from over 33,000 facilities:
  - 5,168 Hospitals
  - 2,733 Sub Acute Care Facilities
  - 21,796 Ambulatory Facilities
  - 2,293 Home Health Care Facilities
  - 177 Free Standing Data Centers
- Market share and purchasing plan data for over 95 software applications and technologies
- New for 2008:
  - Applications: Bed Management, Single Sign-On
  - Statistics
  - Number of Births
  - Number of Outpatient Visits at the Hospital
  - Total Number of Discharges
  - Total Number of Patient Days

- New Types of Physicians (both the hospitals and systems)
- Number of Hospitalists
- Number of Residents
- New IT FTEs
- RCM Support
- EMR Support
- Chief Medical Officers, Chief Nursing Heads, HR Head and OB Head Contacts
- CPOE Usage Details By Order Type
- % of Medical Records that are Electronic
- % of Physicians Using Structured Templates in the CDSS
- Use of Consumer Dashboards
- By Component of a Dashboard the % of Physicians Accessing
- Patient Revenue By Percentage at the Hospital
- Consolidation of Bar Coding and RFID Data
- Details about Items Tagged for Medication Administration
- Details on Systems Taking Advantage of the Relaxation In the Stark Law To Offer
- EMRs to Non-Owned Clinics
- Software Being Remote Hosted (e.g. Perot is remote hosting the Mckesson software)

<u>2007 HIMSS Analytics Database (derived from the Dorenfest IHDS+ Database) (Access 2003)</u>

- Demographic and IT data from over 33,000 facilities:
  - 5,073 Hospitals
  - 2,940 Sub Acute Care Facilities
  - 50,458 Ambulatory Facilities
  - 2,128 Home Health Care Facilities
  - 178 Free Standing Data Centers
- Market share and purchasing plan data for over 90 software applications and technologies
- New for 2007:
  - Applications: Radiology - Orthopedic, Single Sign-On
  - IT Director and Quality Head
  - Next Generation RCM
  - Construction Plans
  - IV Pump Safety Software
  - Plans for Telecommunication

<u>2006 HIMSS Analytics Database (derived from the Dorenfest IHDS+ Database) (Access 2003)</u>

- Demographic and IT data from over 32,000 facilities:
  - 5,082 Hospitals
  - 3,017 Sub Acute Care Facilities
  - 19,714 Ambulatory Facilities
  - 2,055 Home Health Care Facilities
  - 286 Free Standing Data Centers

- Market share and purchasing plan data for over 90 software applications and technologies
- New for 2006:
    - Ambulatory Laboratory, Ambulatory Pharmacy, Ambulatory Radiology , Document
    - Management- Business Office, Document Management- HIM, Document
    - Management- HR, Electronic Forms- Business Office, Electronic Forms- HIM,
    - Electronic Forms-HR, Outsourced Transcription, Browser, DBMS, Email, Interface
    - Engine, Turnkey Portal and Web Development Tool Applications
    - Chief Medical Information Officer and Head of Cardiology
    - Information Exchange Initiatives
    - IV Pumps
    - PC Blades
    - Additional information in Clinical Decision Support
    - Expanded Bar Coding Information
    - Added Breakdown of Physicians

<u>2005 HIMSS Analytics Database (derived from the Dorenfest IHDS+ Database) (Access 2000) (Access 2003)</u>

- Demographic and IT data from over 30,000 facilities:
    - 4010 Hospitals
    - 2875 Sub Acute Care Facilities
    - 17,846 Ambulatory Facilities
    - 1,853 Home Health Care Facilities
- Market share and purchasing plan data for over 100 software applications and technologies
- New for 2005:
    - Data Center hardware installation information
    - Disaster Recovery Plans
    - Details on Physician Use of IT
    - Data Storage Environment details
    - Expanded Wireless and Mobile Device information

<u>The Seventh Dorenfest Complete IHDS+ Database (2004 Data) (Access 2000) (Access 2003)</u>

- Medical Administration and Bar Coding
- CPOE has 2 levels: Prescription Only and Prescription and most other orders
- Annual operating expense for each acute care hospital and the % of the anual hospital operating expense spent on I.T.
- New Software Applications:
    - HIS System
    - Electronic Medication Administration Record (EMAR) System
    - Cardiology PACS System
    - Ambulatory Electronic Medical Record (EMR) System
    - Ambulatory PACS System

The Sixth Dorenfest Complete IHDS+ Database (2003 Data) (Access 97) (Access 2000)

- 5 Additional Contact Names and Email Addresses for each IHDS
- 17 Additional Contact Names and Email Addresses for each Hospital
- Software Installation Information for 8 PACS Modalities, including imaging volume, data storage and purchase plans
- Strategies surrounding CPOE, Patient Safety, and HIPAA

The Fifth Dorenfest Complete IHDS+ Database (2002 Data) (Access 97) (Access 2000)

- Updated Records From 2001
- HIPAA Compliance
- Patient Safety Initiatives
- Physician Usage of IT

The Fourth Dorenfest Complete IHDS+ Database (2001 Data) (Access 97) (Access 2000)

- Updated Records From 2000
- Location of Hardware
- Technological (LAN/WAN) Plans
- Telemedicine

The Third Dorenfest Complete IHDS+ Database (2000 Data) (Access 97) (Access 2000)

- Updated Records From 1999
- Additional Information on IT Budgets and FTEs

The Second Dorenfest Complete IHDS+ Database (1999 Data) (Access 97) (Access 2000)

- Updated Records From 1998
- Additional Information on the Parent-Child Relationship
- Handheld Devices

The First Dorenfest Complete IHDS+ Database (1998 Data) (Access 97) (Access 2000)

- Updated Records From 1994-1995
- Parent-Child Relationships between approximately 1500 IHDS and 35,000 Facilities
- Collaborative Relationships
- Additional Demographic Information
- Enterprise-wide Systems
- Servers
- IT Department Data (Budget, FTEs, etc.)

The 1994-1995 Dorenfest 3000+ Database (Access 97) (Access 2000)

- Updated Records From 1993-1994
- Networking Information
- Detailed Data on Computerized Patient Record
- Computing Architecture
- Imaging Systems
- Physician usage of IT
- Electronic Links
- Integrated Healthcare Delivery System Affiliation
- Systems Integration
- Overall Changes in IT Strategy and Healthcare Reforms
- Additional Hardware Data
- Application Status

The 1993-1994 Dorenfest 3000+ Database (Access 97) (Access 2000)

- Updated Records From 1992-1993
- Additional Consulting Information
- Additional Key Personnel
- Ambulatory Facility Demographic and IT Data
- Information on External Service Providers
- Summary of Hardware Data
- Managed Care IT

The 1992-1993 Dorenfest 3000+ Database (Access 97) (Access 2000)

- Updated Records From 1991-1992
- Additional Key Personnel
- Additional Demographic Sizing Data
- The 1991-1992 Dorenfest 3000+ Database (Access 97) (Access 2000)
- Updated Records From 1990-1991
- Application Integration
- Hospital-wide Integration
- Private Branch Exchange
- Patient Care Technology
- The 1990-1991 Dorenfest 3000+ Database (Access 97) (Access 2000)
- Updated Records From 1989-1990
- Hardware Purchasing Plans
- Hospital Connectivity

The 1989-1990 Dorenfest 3000+ Database (Access 97) (Access 2000)

- Updated Records From 1988-1989
- Additional Budget Information
- Additional LAN Detail

- The 1988-1989 Dorenfest 3000+ Database (Access 97) (Access 2000)
- Updated Records From 1987-1988
- Additional Key Personnel
- Detailed Software Plan Data
- LAN Use

The 1987-1988 Dorenfest 3000+ Database (Access 97) (Access 2000)

- Updated Records From 1986-1987
- Names and Titles of Key Personnel
- Names and Titles of Steering Committee Members
- Computers and Printers in Use
- The 1986-1987 Dorenfest 3000+ Database (Access 97) (Access 2000)
- Demographic Information for Approximately 3000 Hospitals
- Software Vendors and Products in Use or Planned Use
- Hardware Data
- Consultants Used

foundation@himss.org | © HIMSS Foundation 2010 | 312-915-9523
Database Listing http://www.himss.org/DorenfestInstitute/DatabaseListing.aspx
Last access 4/14/2011 4:58 PM

B.3 Results ME for Excel output

The tables are associated to the Data Sets shown in Table 17.

Bass Parameters

Total Market Potential	3000	**Total number of potential adopters before period 1.**
Market Penetration Before Period 1	137	**Total number of actual adopters before period 1.**
Market Growth Rate	0.0%	**Growth rate of the market potential.**
p coefficient	8.9389E-18	**Coefficient p (advertising…) of the Bass model.**
q coefficient	0.38322371	**Coefficient q (social contagion) of the Bass model.**

Model Goodness-of-Fit

Pearson's R^2 (correlation coefficient) of the model.

Pearson's R^2	0.98421344

Figure B.3.1 Parameter estimation Data Set 1

Bass Parameters

Total Market Potential	4500	**Total number of potential adopters before period 1.**
Market Penetration Before Period 1	265	**Total number of actual adopters before period 1.**
Market Growth Rate	0.5%	**Growth rate of the market potential.**
p coefficient	0.00507661	**Coefficient p (advertising…) of the Bass model.**
q coefficient	0.24371676	**Coefficient q (social contagion) of the Bass model.**

Model Goodness-of-Fit

Pearson's R^2 (correlation coefficient) of the model.

Pearson's R^2	0.73333315

Figure B.3.2 Parameter estimation Data Set 2

Bass Parameters

Total Market Potential	5500	**Total number of potential adopters before period 1.**
Market Penetration Before Period 1	130	**Total number of actual adopters before period 1.**
Market Growth Rate	0.1%	**Growth rate of the market potential.**
p coefficient	0.0080293	**Coefficient p (advertising…) of the Bass model.**
q coefficient	0.18090428	**Coefficient q (social contagion) of the Bass model.**

Model Goodness-of-Fit

Pearson's R^2 (correlation coefficient) of the model.

Pearson's R^2	0.78975492

B.3.3 Table for parameter estimation Data Set 3

Bass Parameters

Total Market Potential	5500	**Total number of potential adopters before period 1.**
Market Penetration Before Period 1	1000	**Total number of actual adopters before period 1.**
Market Growth Rate	0.1%	**Growth rate of the market potential.**
p coefficient	8.4245E-17	**Coefficient p (advertising…) of the Bass model.**
q coefficient	0.4708715	**Coefficient q (social contagion) of the Bass model.**

Model Goodness-of-Fit

Pearson's R^2 (correlation coefficient) of the model.

Pearson's R^2	0.99999857

B.3.4 Table for parameter estimation Data Set 4

Bass Parameters

Total Market Potential	5500	**Total number of potential adopters before period 1.**
Market Penetration Before Period 1	831	**Total number of actual adopters before period 1.**
Market Growth Rate	0.1%	**Growth rate of the market potential.**
p coefficient	7.9971E-17	**Coefficient p (advertising…) of the Bass model.**
q coefficient	0.31555087	**Coefficient q (social contagion) of the Bass model.**

Model Goodness-of-Fit

Pearson's R^2 (correlation coefficient) of the model.

Pearson's R^2	0.87235682

B.3.5 Table for parameter estimation Data Set 5

Bass Parameters

Total Market Potential	5500	**Total number of potential adopters before period 1.**
Market Penetration Before Period 1	20	**Total number of actual adopters before period 1.**
Market Growth Rate	0.1%	**Growth rate of the market potential.**
p coefficient	0.03039912	**Coefficient p (advertising…) of the Bass model.**
q coefficient	0.08190842	**Coefficient q (social contagion) of the Bass model.**

Model Goodness-of-Fit

Pearson's R^2 (correlation coefficient) of the model.

Pearson's R^2	0.85691755

B.3.6 Table for parameter estimation Data Set 6

Appendix C. Formulation

C.1 Vensim model formulation output – Stage 1

Formulation for MMIS diffusion model Data Set 3

(01)Adopters A= INTEG (Hospital AR, Initial adopters)
Units: member

(02)Adopters influence Type I=Adopters A/Total Population N
Units: 1

(03)external influence=p coefficient*Potential Adopters P
Units: member/Year

(04)Hospital AR= external influence + internal influence
Units: member/Year

(05)Initial adopters= INITIAL(130)
Units: member

(06)internal influence=Adopters influence Type I*q coefficient*Potential Adopters P
Units: member/Year

(07)p coefficient=0.0080293
Units: 1/Year

(10)Potential Adopters P= INTEG (-Hospital AR,Total Population N-130)
Units: member

(11)q coefficient=0.180904
Units: 1/Year

(12)Total Population N=5500
Units: member

C.2 Vensim model formulation output – Stage 2

(01) A initial=500
Units: member [0,3000,150]

(2) adopter influence=Adopters A/Total Population N
Units: 1

(3) Adopters A= INTEG (Hospital AR,A initial)
Units: member

(4)average H IS budget=IS Budget*average H revenue
Units: dollars/Year

(5) average H operating expenses=2.62364e+008
Units: dollars/Year

(6) average H revenue=2.7e+008
Units: dollars/Year [0,2e+009,1e+006]

(7) awareness=1
Units: Dmnl [0,10,1]

(8) complexity and interoperability issues=1
Units: Dmnl [0,3,1]

(9) distributors and GPOs = WITH LOOKUP (Time,([(0,0)-(50,200)],(0,0),(0,0),(1,5),(3,23),(11,89),(15,120),(20,150),(25,160),(30,170),(40,180),(50,190)))
Units: 1 [0,?]

(10) distributors and GPOs influence = WITH LOOKUP (distributors and GPOs,([(0,0)-(200,1)],(0,0),(1,0.2),(14.6789,0.5),(50,0.7),(100,0.75),(150,0.8),(200,0.9)))
Units: Dmnl

(11) expected gains by process=productivity improvement factor*H SCM operating costs
Units: dollars/Year

(12) external factors influence=(m5+m6)/2
Units: Dmnl

(13) external influence N=0.02
Units: 1/Year [0,1,0.01]

(14) external source=external factors influence*external influence N*Potential Adopters P
Units: member/Year

(15) government intervention=1
Units: 1 [0,10,1]

(16) H expected benefits=expected gains by process
Units: dollars/Year

(17) H expected costs=H IdS implementation costs*EXP(increase SCM expending*Time)
Units: dollars/Year

(18) H expected gain=H expected benefits-H expected costs
Units: dollars/Year

(19) H IdS implementation costs=IdS factor*average H IS budget
Units: dollars/Year

(20) H IdS Use = WITH LOOKUP (adopter influence,([(0,0)-(1,1)],(0,0),(0,0),(0,0),(0.25,0.3),(0.5,0.5),(0.7,0.6),(1,1)))
Units: Dmnl

(21) "H organizational readiness (P)"=process fraction*awareness
Units: Dmnl

(22) "H organizational readiness (T)"=("H organizational readiness (P)"+H technology penetration factor)/2
Units: Dmnl

(23) H relative advantage= WITH LOOKUP (H expected gain,([(0,0)-(1.5e+007,1)],(0,0),(94117.6,0.0106762),(845066,0.170819),(1.2676e+006,0.252669),(2.51172e+006,0.423488),(3.8028e+006,0.594306),(4.9765e+006,0.715302),(6.10325e+006,0.790036),(7.48822e+006,0.882562),(8.6854e+006,0.939502),(9.97647e+006,0.95),(1.5e+007,1)))
Units: Dmnl

(24) H SCM operating costs=average H operating expenses*IdS factor
Units: dollars/Year

(25) H technology penetration factor=0.4
Units: Dmnl [0,1,0.05]

(26) Hospital AR=external source+internal source
Units: member/Year [0,?]

(27) IdS factor=0.05
Units: Dmnl [0,1,0.01]

(28) increase SCM expending=0.01
Units: 1/Year [0,1,0.01]

(29) industry pressure = WITH LOOKUP (distributors and GPOs influence,([(0,0)(1,1)],(0,0),(0.189602,0.307018),(0.3,0.45),(0.400612,0.539474),(0.5,0.7),(0.620795,0.789474),(1,0.9)))
Units: Dmnl

(30) internal influence N=0.32
Units: 1/Year [0,1,0.01]

(31) internal source=internal influence N*Potential Adopters P*organization related factors influence*technology related factors influence
Units: member/Year

(32) IS Budget=0.03
Units: Dmnl [0,1,0.01]

(33) m1="H organizational readiness (T)"
Units: Dmnl

(34) m2=H relative advantage
Units: Dmnl

(35) m3=TP relative advantage
Units: Dmnl

(36) m4=TP readiness*complexity and interoperability issues
Units: Dmnl

(37) m5=industry pressure
Units: Dmnl

(38) m6=government intervention*manufacturer influence
Units: Dmnl

(39) manufacturer influence = WITH LOOKUP (manufacturers,([(0,0)-(7000,1)],(0,0),(0,0),(214.067,0.267544),(1000,0.4),(3000,0.5),(3831.8,0.605263),(4067.28,0.653509),(4752.29,0.701754),(6000,0.780702),(7000,0.9)))
Units: Dmnl

(40) manufacturers = WITH LOOKUP (Time,([(0,0)-(50,6000)],(0,0),(1,5),(2,150),(4,160),(10,236),(15,368),(20,1000),(25,2000),(32,3631.58),(50,6000)))
Units: 1

(41) organization related factors influence=((m1)+m2)/2
Units: 1

(42) P initial=2500
Units: member [0,3000,150]

(43) Potential Adopters P= INTEG (-Hospital AR,P initial)
Units: member

(44) process fraction = WITH LOOKUP (H IdS Use,([(0,0)-(1,0.6)],(0,0),(0.1,0.005),(0.2,0.01),(0.3,0.1),(0.4,0.15),(0.5,0.2),(0.6,0.3),(0.7,0.4),(1,0.5)))
Units: Dmnl

(45) productivity improvement factor = WITH LOOKUP (H IdS Use,([(0,0)-(1,0.8)],(0,0),(0,0),
(0.1,0.02),(0.251765,0.116726),(0.348235,0.182206),(0.404706,0.239146),(0.458824,0.301779),
(0.496471,0.335943),(0.536471,0.387189),(0.6,0.449822),(0.649412,0.492527),
(0.703529,0.543772),(0.762353,0.600712),(0.858824,0.680427),(1,0.8)))
Units: 1

(46) technology providers = WITH LOOKUP (Time,([(0,0)-
(50,80)],(0,0),(0,0),(0,0),(1,1),(3,2),(5,4),(10,8),(13,13),(18,23),(27,42),(40,60),(50,70)))
Units: member

(47) technology related factors influence=(m3*m4)
Units: 1

(48) Total Population N=Adopters A+Potential Adopters P
Units: member

(49) TP expected benefits=H expected costs
Units: dollars/Year

(50) TP expected costs = WITH LOOKUP (H IdS Use,([(0,0)-(1,1e+006)],(0,1e+006),
(0.0447059,832740),(0.202353,302491),(0.334118,231317),(0.44,199288),(0.607059,160142),
(0.717647,131673),(0.809412,124555),(0.882353,124555),(1,100000)))
Units: dollars/Year

(51) TP expected gain=TP expected benefits-TP expected costs
Units: dollars/Year

(52) TP readiness = WITH LOOKUP (technology providers,([(0,0)-
(70,6)],(0,0),(5,1),(10,1.5),(18.4098,2.18421),(30,3),(40,3.5),(50,4),(60,4.5),(70,5)))
Units: Dmnl

(53) TP relative advantage= WITH LOOKUP (TP expected gain,([(0,0)-
(2e+006,1)],(0,0),(10000,0.1),(20000,0.1),(50000,0.2),(100000,0.3),(200000,0.4),
(564706,0.654804),(1.00235e+006,0.779359),(2e+006,0.9)))
Units: 1

C.3 Formulation description

C.3.1 Graphical functions (by model component)

The graphical functions are the main model assumptions regarding the main variables within the simulation model. For each graphical function different function shapes and distributions were tested following the steps described in Section 5.2. For example the range for the graphical

functions associated with the manufacturer population as well as distributors and technology providers was supported by industry reports from HIDA.

Component 1 graphical functions

(40) manufacturers = WITH LOOKUP (Time,([(0,0)-(50,6000)],(0,0),(1,5),(2,150),
(4,160),(10,236),(15,368),(20,1000),(25,2000),(32,3631.58),(50,6000)))
Units: 1

(9) distributors and GPOs = WITH LOOKUP (Time,([(0,0)-
(50,200)],(0,0),(0,0),(1,5),(3,23),(11,89),(15,120),(20,150),(25,160),(30,170),(40,180),(50,190)))
Units: 1 [0,?]

(10) distributors and GPOs influence = WITH LOOKUP (distributors and GPOs,([(0,0)-
(200,1)],(0,0),(1,0.2),(14.6789,0.5),(50,0.7),(100,0.75),(150,0.8),(200,0.9)))
Units: Dmnl

(29) industry pressure = WITH LOOKUP (distributors and GPOs influence,([(0,0)(1,1)],(0,0),
(0.189602,0.307018),(0.3,0.45),(0.400612,0.539474),(0.5,0.7),(0.620795,0.789474),(1,0.9)))
Units: Dmnl

(39) manufacturer influence = WITH LOOKUP (manufacturers,([(0,0)-
(7000,1)],(0,0),(0,0),(214.067,0.267544),(1000,0.4),(3000,0.5),(3831.8,0.605263),(4067.28,0.65
3509),(4752.29,0.701754),(6000,0.780702),(7000,0.9)))
Units: Dmnl

Component 2 graphical functions

(46) technology providers = WITH LOOKUP (Time,([(0,0)-
(50,80)],(0,0),(0,0),(0,0),(1,1),(3,2),(5,4),(10,8),(13,13),(18,23),(27,42),(40,60),(50,70)))
Units: member

(50) TP expected costs = WITH LOOKUP (H IdS Use,([(0,0)-(1,1e+006)],(0,1e+006),
(0.0447059,832740),(0.202353,302491),(0.334118,231317),(0.44,199288),(0.607059,160142),
(0.717647,131673),(0.809412,124555),(0.882353,124555),(1,100000)))
Units: dollars/Year

(52) TP readiness = WITH LOOKUP (technology providers,([(0,0)-
(70,6)],(0,0),(5,1),(10,1.5),(18.4098,2.18421),(30,3),(40,3.5),(50,4),(60,4.5),(70,5)))
Units: Dmnl

(53) TP relative advantage= WITH LOOKUP (TP expected gain,([(0,0)-(2e+006,1)],(0,0),(10000,0.1),(20000,0.1),(50000,0.2),(100000,0.3),(200000,0.4),(564706,0.654804),(1.00235e+006,0.779359),(2e+006,0.9)))
Units: 1

Component 3 graphical functions

(44) process fraction = WITH LOOKUP (H IdS Use,([(0,0)-(1,0.6)],(0,0),(0.1,0.005),(0.2,0.01),(0.3,0.1),(0.4,0.15),(0.5,0.2),(0.6,0.3),(0.7,0.4),(1,0.5)))
Units: Dmnl
(23) H relative advantage= WITH LOOKUP (H expected gain,([(0,0)-(1.5e+007,1)],(0,0),(94117.6,0.0106762),(845066,0.170819),(1.2676e+006,0.252669),(2.51172e+006,0.423488),(3.8028e+006,0.594306),(4.9765e+006,0.715302),(6.10325e+006,0.790036),(7.48822e+006,0.882562),(8.6854e+006,0.939502),(9.97647e+006,0.95),(1.5e+007,1)))
Units: Dmnl

(45) productivity improvement factor = WITH LOOKUP (H IdS Use,([(0,0)-(1,0.8)],(0,0),(0,0),(0.1,0.02),(0.251765,0.116726),(0.348235,0.182206),(0.404706,0.239146),(0.458824,0.301779),(0.496471,0.335943),(0.536471,0.387189),(0.6,0.449822),(0.649412,0.492527),(0.703529,0.543772),(0.762353,0.600712),(0.858824,0.680427),(1,0.8)))
Units: 1

Component 4 graphical functions

(20) H IdS Use = WITH LOOKUP (adopter influence,([(0,0)-(1,1)],(0,0),(0,0),(0,0),(0.25,0.3),(0.5,0.5),(0.7,0.6),(1,1)))
Units: Dmnl

C.3.2 Parameters (by model component)

The parameters are the simulation model initial conditions. For each parameter different range values were tested following the steps described in Section 5.2. The parameters were developed based on industry reports and information extracted from the 2008 HIMSS DB. For example the information associated to the hospital revenue and operating expenses extracted from the 2008 HIMSS DB was used to develop parameters (5) and (6). Technology penetration data also extracted from this database was used to estimate the value of the parameter (25). The

parameters within Component 4 (C4) were based on previous results from Stage 1 and information provided in AHA reports.

Component 1
(15) government intervention=1
Units: 1 [0,10,1]

Component 2
(8) complexity and interoperability issues=1
Units: Dmnl [0,3,1]

Component 3
(5) average H operating expenses=2.62364e+008
Units: dollars/Year

(6) average H revenue=2.7e+008
Units: dollars/Year [0,2e+009,1e+006]

(7) awareness=1
Units: Dmnl [0,10,1]

(25) H technology penetration factor=0.4
Units: Dmnl [0,1,0.05]

(27) IdS factor=0.05
Units: Dmnl [0,1,0.01]

(28) increase SCM expending=0.01
Units: 1/Year [0,1,0.01]

(32) IS Budget=0.03
Units: Dmnl [0,1,0.01]

Component 4
(13) external influence N=0.02
Units: 1/Year [0,1,0.01]

(30) internal influence N=0.32
Units: 1/Year [0,1,0.01]

(01) A initial=500
Units: member [0,3000,150]

(42) P initial=2500
Units: member [0,3000,150]

Appendix D. Sensitivity analysis results

D1. Sensitivity analysis tests

The sensitivity analysis was developed based on a series of tests. Four tests were initially developed and a fifth one completed the set. The steps followed to perform the sensitivity analysis tests are described in Section 5.3.3 and include the following tests:

- Test 1, sensitivity analysis test for parameters within group 1, remaining parameters were kept unchanged.
- Test 2, sensitivity analysis test for parameters within group 2, remaining parameters were kept unchanged.
- Test 3, sensitivity analysis test for parameters within group 3, remaining parameters were kept unchanged.
- Test 4, sensitivity analysis test for parameters within group 4, remaining parameters were kept unchanged.
- Test 5, sensitivity analysis test for parameters within groups 1,2 and 3 remaining parameters were kept unchanged.

D.2 Vensim sensitivity analysis output

The results for the Adopters A (output variable) for tests 1, 2 and 3 are shown in the following figures.

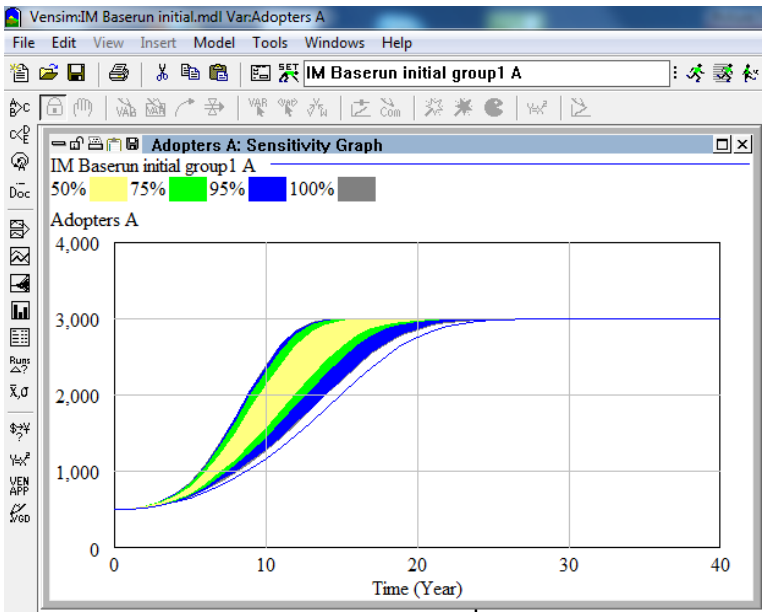


Figure D.2.1 Sensitivity analysis graph test 1

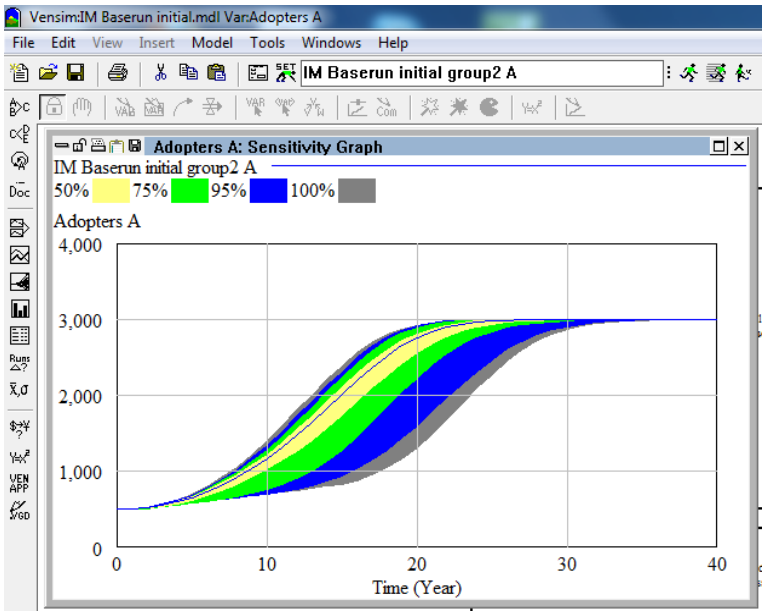


Figure D.2.2 Sensitivity analysis graph test 2

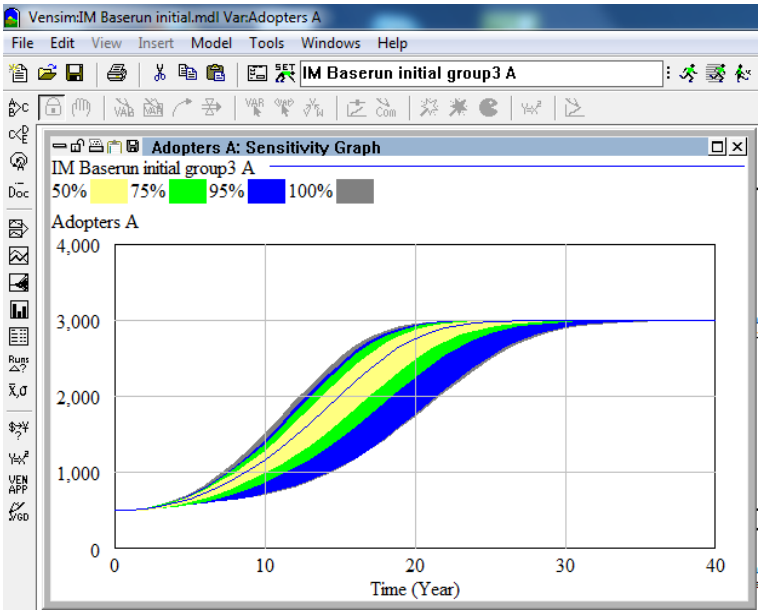


Figure D.2.3 Sensitivity analysis graph test 3

D.3 Correlation Coefficient plots

The data associated to each one of the sensitivity analysis tests was exported to MSO Excel in order to develop the CC plots. The CC plots for both output measures, the adoption rate and the adopter population are included in this section.

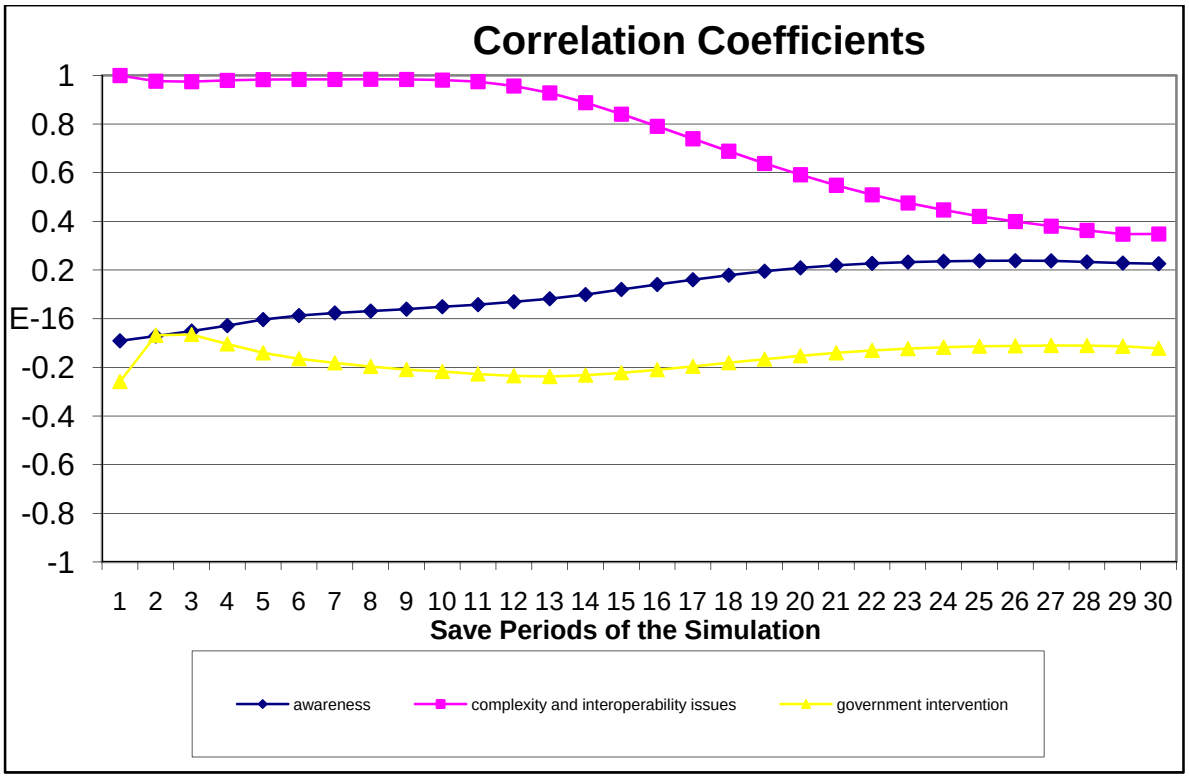


Figure D.3.1 Correlation Coefficient plot for Adopter population – test 1

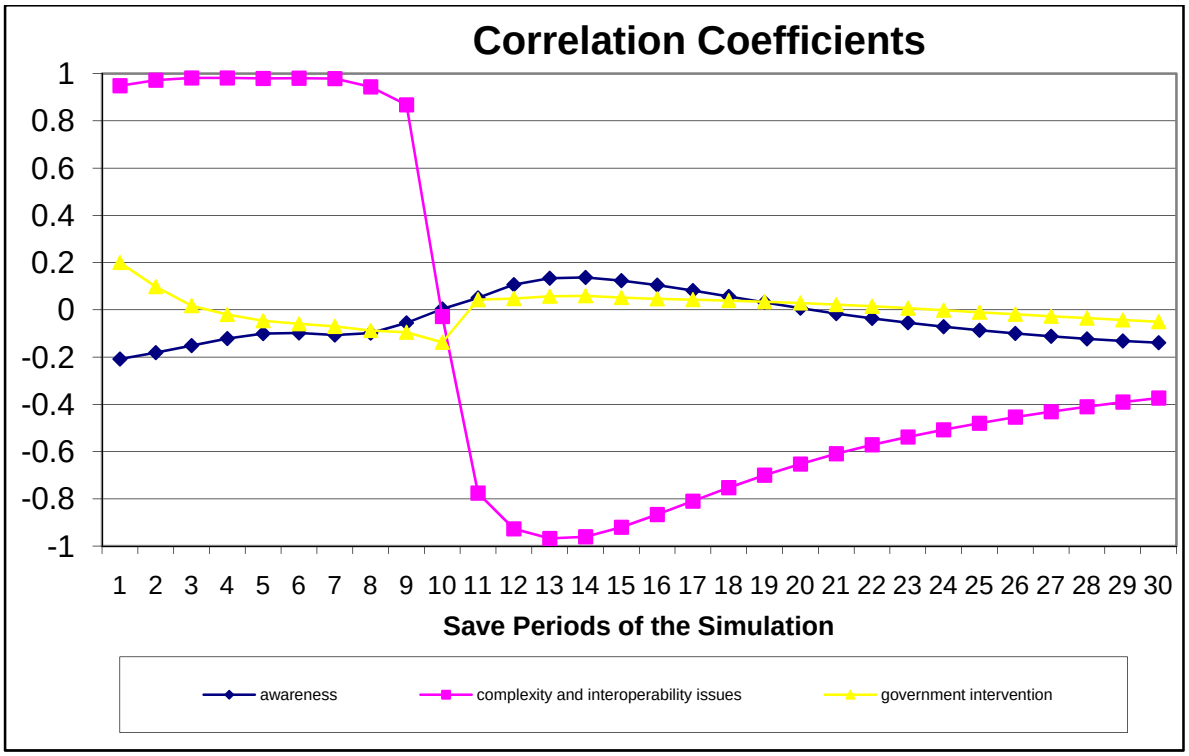


Figure D.3.2 Correlation Coefficient plot for Adoption Rate – test 1

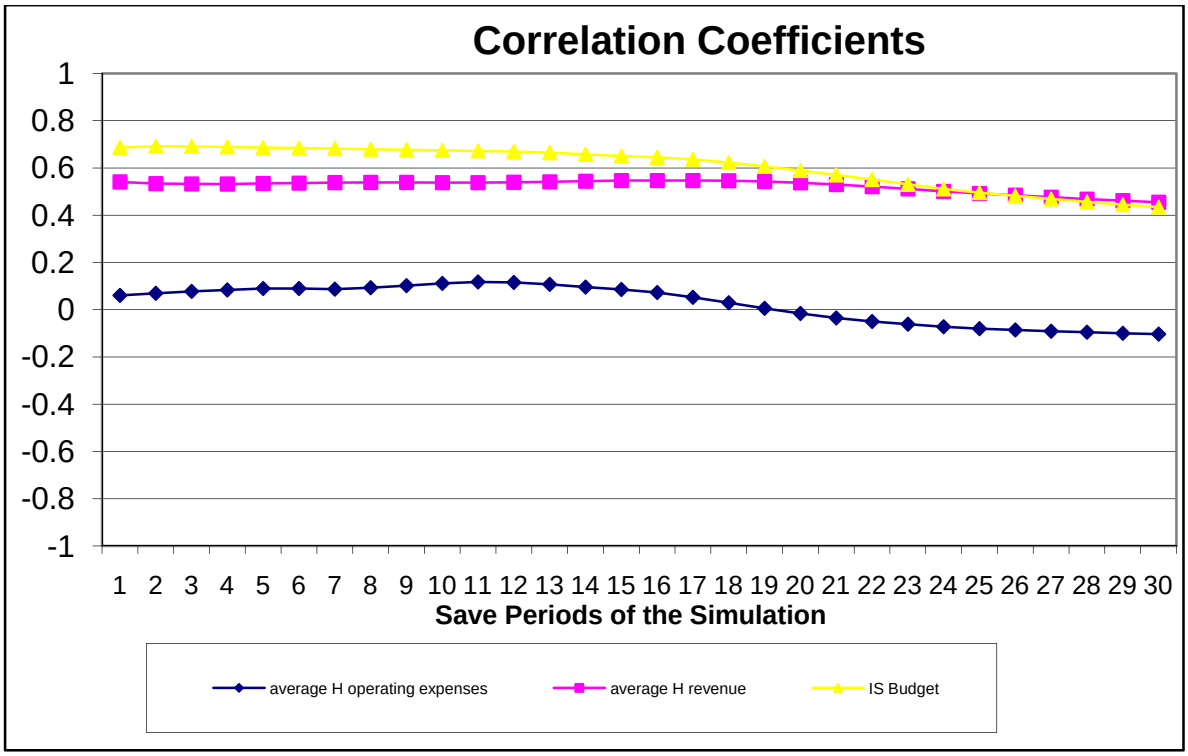


Figure D.3.3 Correlation Coefficient plot for Adopter population – test 2

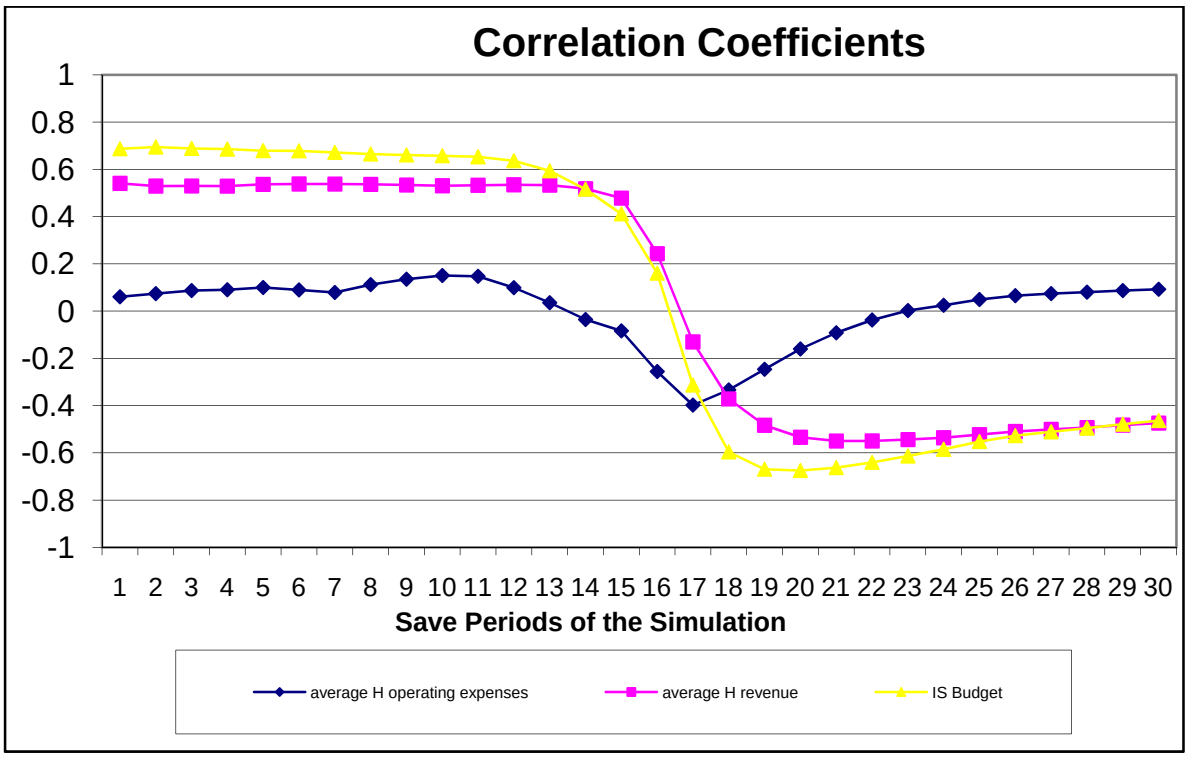


Figure D.3.4 Correlation Coefficient plot for Adoption Rate – test 2

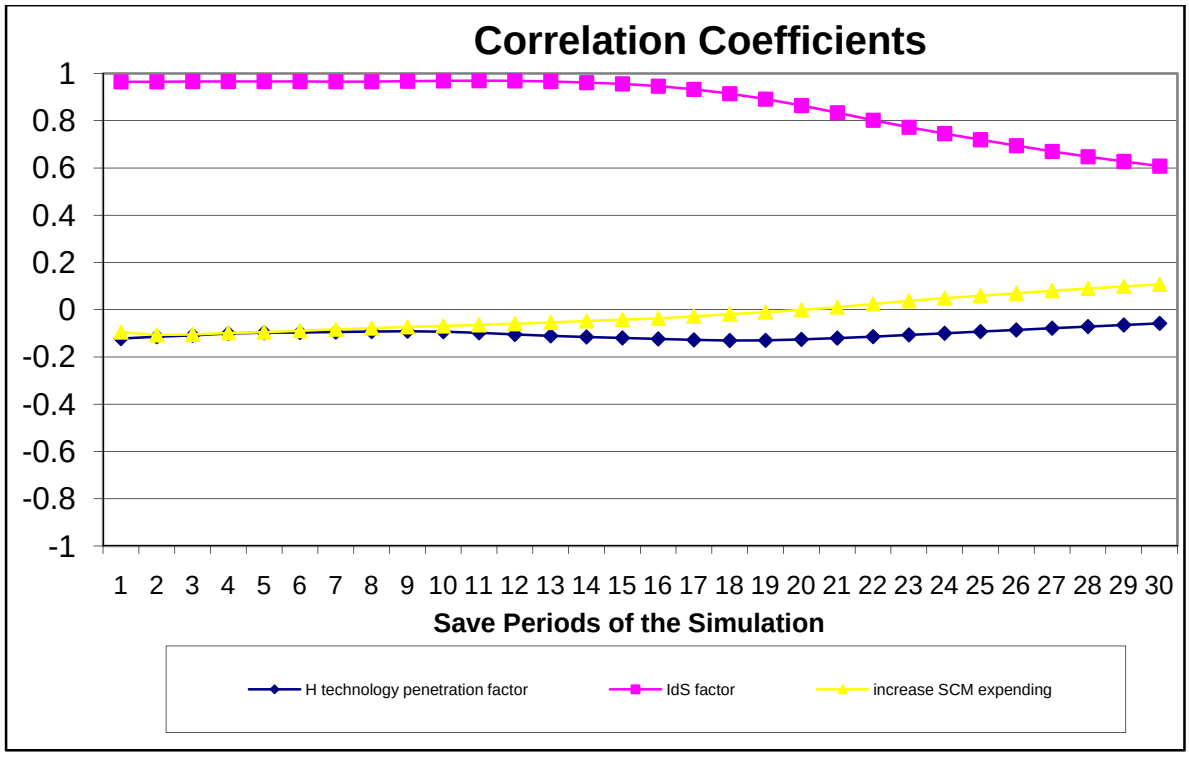


Figure D.3.5 Correlation Coefficient plot for Adopter population – test 3

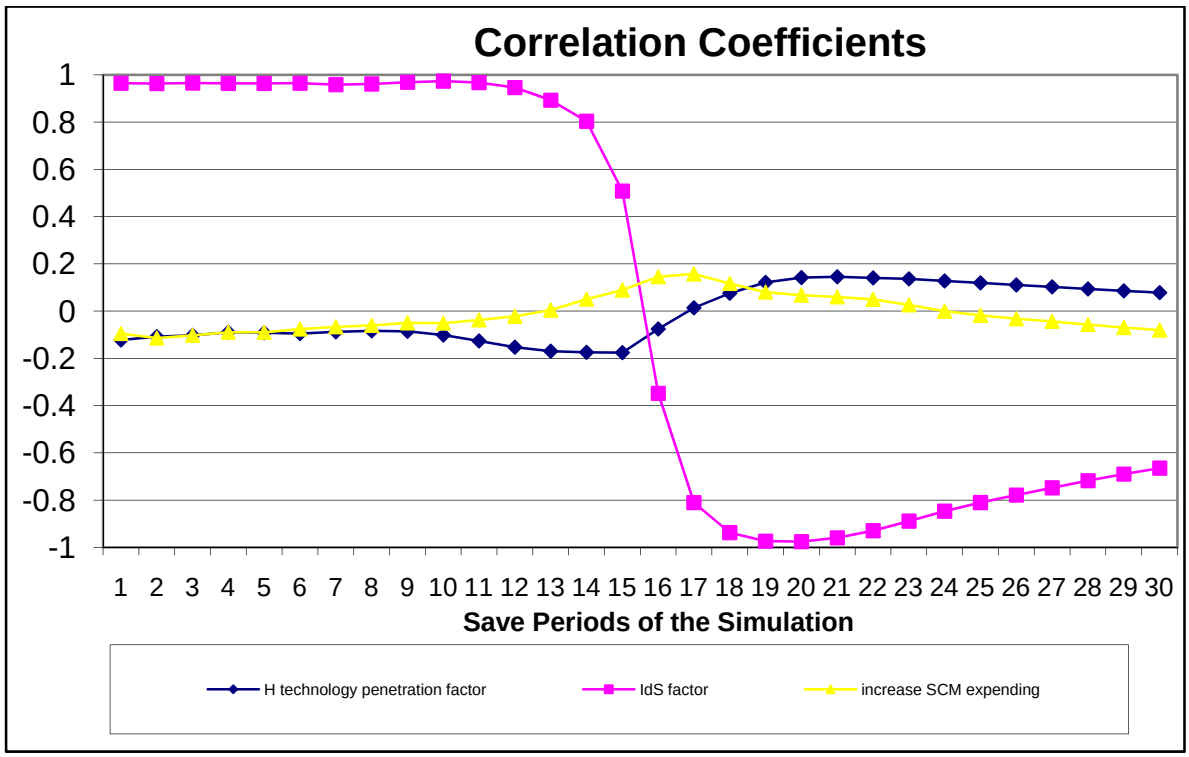


Figure D.3.6 Correlation Coefficient plot for Adoption Rate – test 3

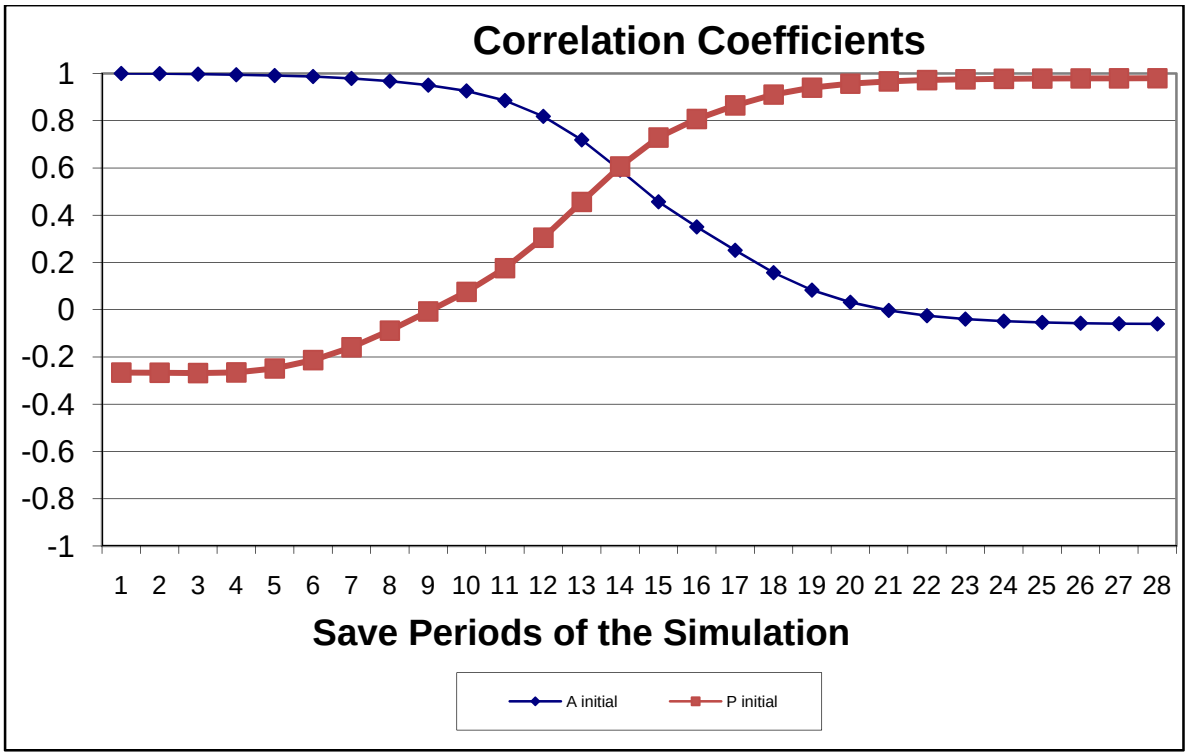


Figure D.3.7 Correlation Coefficient plot for Adopter population – test 4

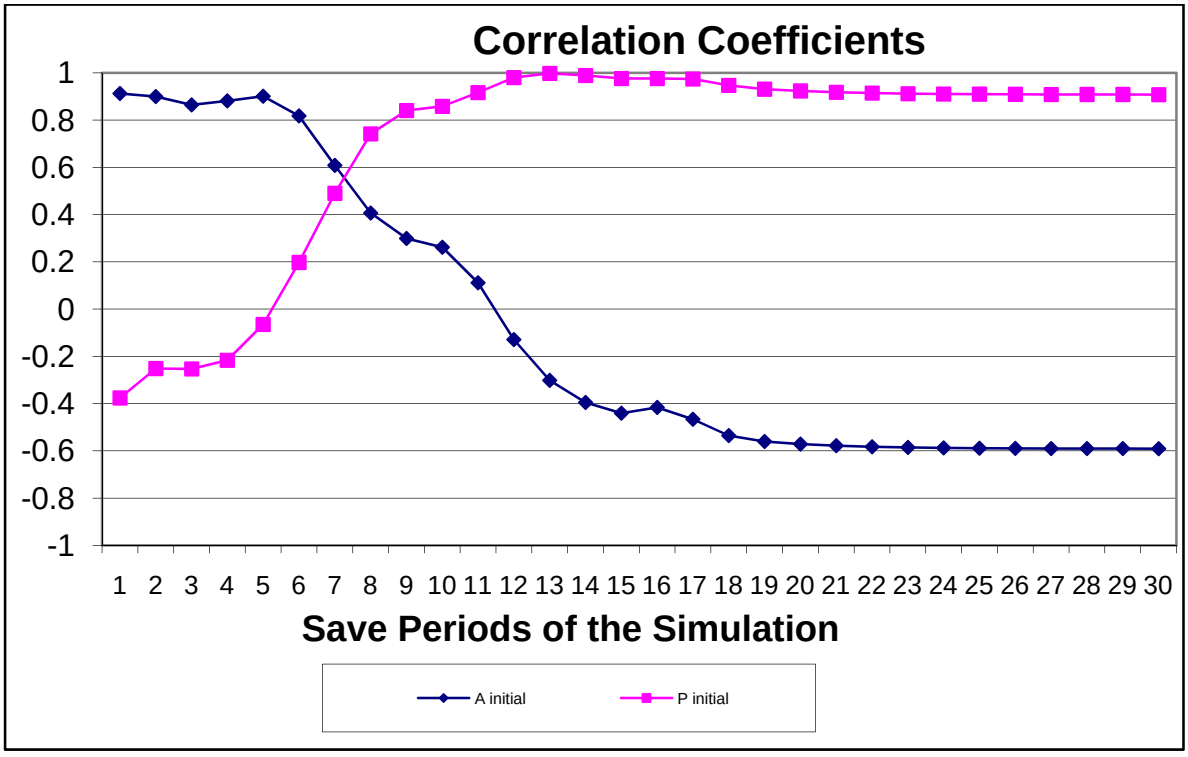


Figure D.3.8 Correlation Coefficient plot for Adoption Rate – test 4

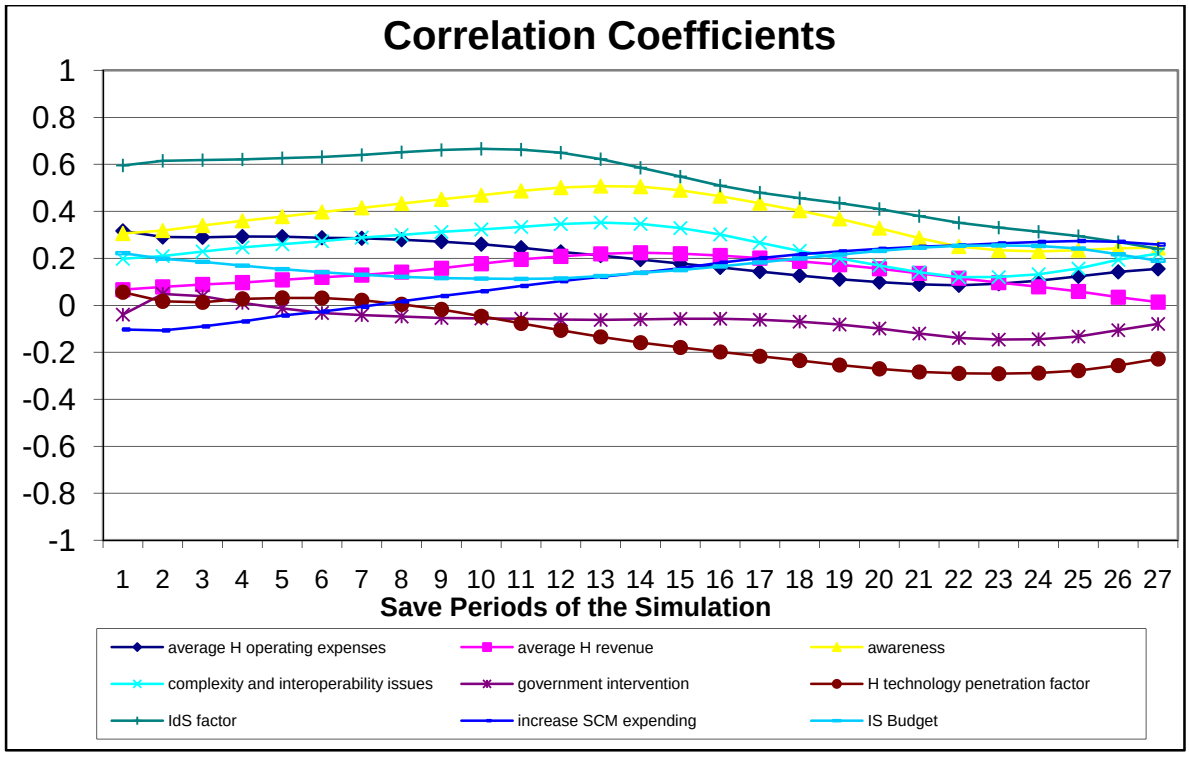


Figure D.3.9 Correlation Coefficient plot for Adopter population – test 5

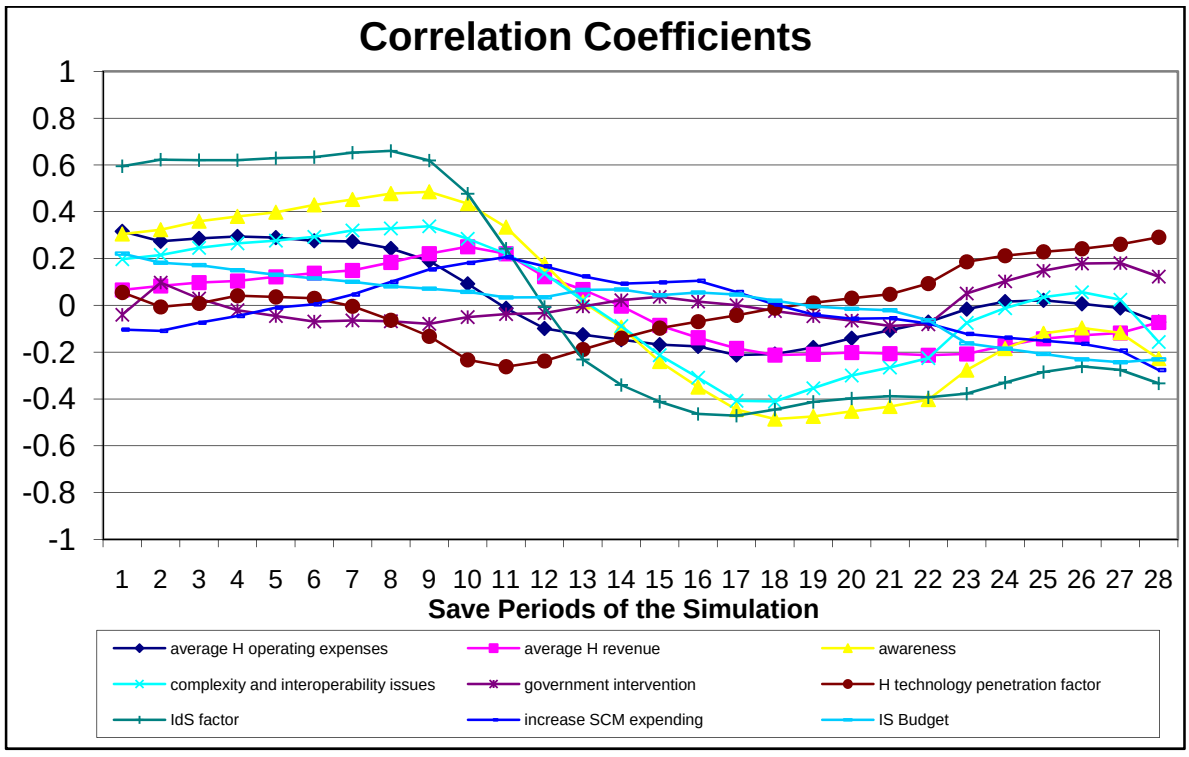


Figure D.3.10 Correlation Coefficient plot for Adoption Rate – test 5

Appendix E. Policy design and testing

E.1 Policies proposed changes

Table E.1.1

Intervention	Policy (Vensim model)	Proposed changes
Policy 1	IM Baserun initial Policy1b	Government intervention STEP function (5,2) and change in manufacturer's graphical function
Policy 2	IM Baserun initial Policy2	Change in technology provider's graphical function
Policy 3	IM Baserun initial Policy3	H technology penetration factor = 0.8 Awareness = 3 IdS Factor = 0.06
Policy combination 1	IM Baserun initial Policy1b and 2	Includes changes for Policy 1b and Policy 2
Policy combination 2	IM Baserun initial Policy2 and 3	Includes changes for Policy 2 and Policy 3
Policy combination 3	IM Baserun initial Policy3 and 1b	Includes changes for Policy 3 and Policy 1b
Policy combination 4	IM Baserun initial combined policy	H technology penetration factor = 0.6 Awareness = 3 IdS factor = 0.07 Government intervention = 3 Complexity and interoperability issues = 2

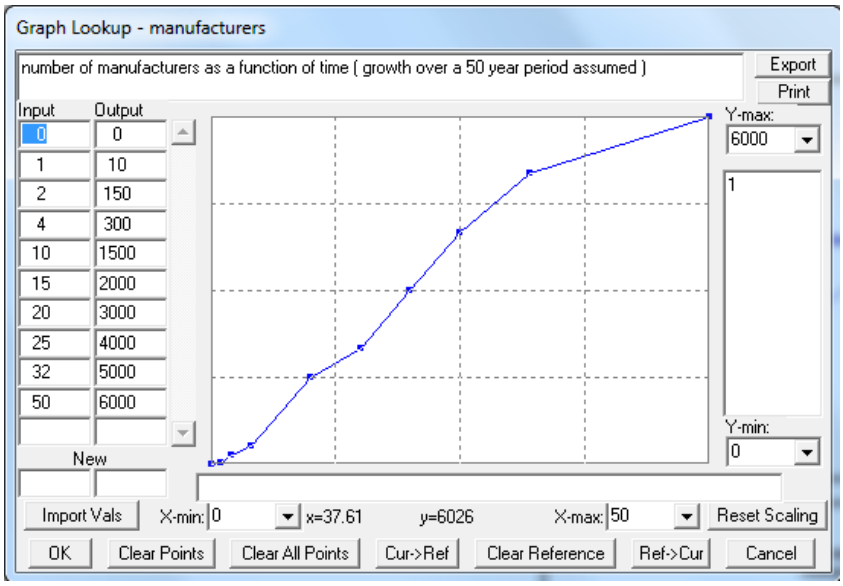


Figure E.1.2 Manufacturer's graphical function proposed change

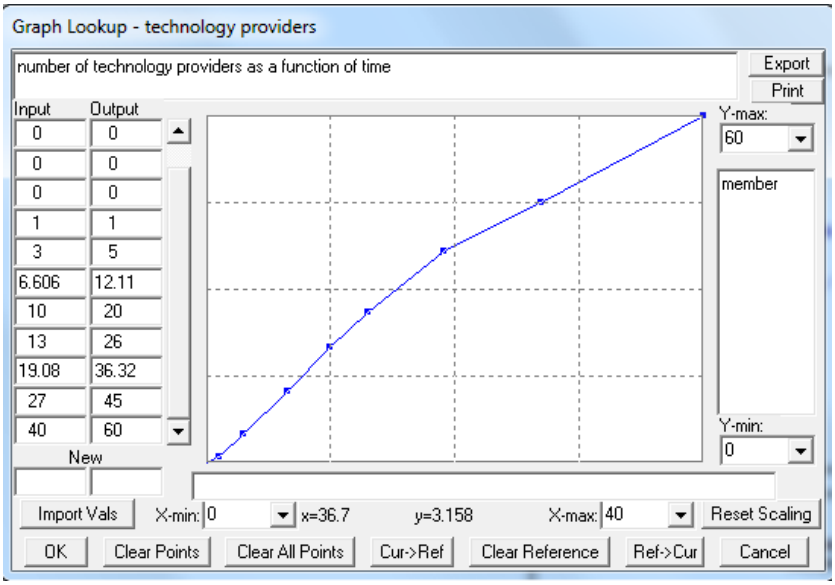


Figure E.1.3 Technology provider's graphical function proposed change

E.2 Detailed description policies supporting data

	IM Baserun initial Policy1a		IM Baserun initial Policy1b	
t	AR	A	AR	A
0	0	500	0.00	500
1	1.79	502	19.00	519
2	5.43	507	53.42	572
3	8.11	515	71.20	644
4	13.13	528	87.87	731
5	19.13	548	110.78	842
6	25.11	573	130.16	972
7	30.35	603	143.92	1116
8	35.86	639	155.69	1272
9	42.10	681	166.42	1438
10	49.47	730	173.54	1612
11	60.93	791	181.59	1794
12	70.90	862	181.20	1975
13	80.55	943	173.40	2148
14	91.92	1035	165.01	2313
15	105.76	1141	157.65	2471
16	121.81	1262	138.79	2610
17	139.05	1401	112.62	2722
18	154.78	1556	86.96	2809
19	165.55	1722	64.41	2874
20	170.80	1893	45.70	2919
21	168.18	2061	31.12	2950
22	157.80	2219	20.11	2971
23	150.55	2369	12.48	2983
24	139.75	2509	7.49	2991
25	120.20	2629	4.35	2995
26	98.11	2727	2.44	2997
27	77.27	2804	1.32	2999
28	58.35	2863	0.68	2999
29	42.90	2906		
30	31.08	2937		
31	21.97	2959		
32	15.08	2974		
33	9.96	2984		
34	6.44	2990		
35	4.07	2994		
36	2.47	2997		
37	1.46	2998		
38	0.84	2999		
39				
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Table E.2.1 Policies Component 1

	IM Baserun initial Policy2		IM Baserun initial Policy3	
t	AR	A	AR	A
0	0	500	0	500
1	19.16	519	32.62	533
2	48.22	567	56.77	589
3	73.65	641	75.31	665
4	95.32	736	111.84	777
5	122.77	859	157.71	934
6	146.48	1006	194.45	1129
7	169.5	1175	226.07	1355
8	197.06	1372	247.96	1603
9	224.39	1597	248.95	1852
10	234.47	1831	237.7	2089
11	227.19	2058	228.44	2318
12	206.78	2265	215.61	2533
13	191.7	2457	167.94	2701
14	163.2	2620	121	2822
15	124.91	2745	80.51	2903
16	89.45	2834	48.51	2951
17	61.17	2895	26.21	2978
18	40.37	2936	12.87	2990
19	25.8	2962	5.815	2996
20	15.88	2977	2.389	2999
21	9.552	2987	0.8868	3000
22	5.634	2993		
23	3.261	2996		
24	1.852	2998		
25	1.033	2999		
26	0.5653	2999		
27				
28				
29				
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Table E.2.2 Policies Components 2 and 3

	IM Baserun initial Policy1b and 2		IM Baserun initial Policy3 and 2	
t	AR	A	AR	A
0	0	500	0	500
1	19.00	519	32.62	533
2	66.81	586	92.24	625
3	103.51	689	161.48	786
4	132.03	821	229.32	1016
5	163.78	985	291.19	1307
6	190.43	1176	347.92	1655
7	216.05	1392	352.79	2008
8	238.07	1630	318.95	2327
9	241.77	1871	277.21	2604
10	229.76	2101	184.52	2788
11	204.84	2306	108.57	2897
12	188.54	2495	57.77	2955
13	156.22	2651	27.35	2982
14	117.00	2768	11.5	2993
15	83.14	2851	4.399	2998
16	56.27	2907	1.518	2999
17	36.56	2944	0.4766	3000
18	23.02	2967		
19	14.08	2981		
20	8.32	2989		
21	4.82	2994		
22	2.74	2997		
23	1.52	2998		
24	0.83	2999		
25				
26				
27				
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Table E.2.3 Policy 1b and 2; Policy 3 and 2

	IM Baserun initial Policy3 and 1b		IM Baserun initial combined policy	
t	AR	A	AR	A
0	0	500	0	500
1	32.46	532	40.66	541
2	75.27	608	81.05	622
3	104.20	712	112.24	734
4	144.81	857	176.24	910
5	190.73	1047	244.58	1155
6	230.70	1278	312.97	1468
7	258.63	1537	352.19	1820
8	262.87	1800	336.11	2156
9	250.31	2050	294.64	2451
10	226.34	2276	241.95	2693
11	217.14	2493	159.18	2852
12	175.81	2669	87.55	2939
13	127.82	2797	39.89	2979
14	87.75	2885	15.14	2994
15	55.22	2940	4.48	2999
16	31.40	2971	0.97	3000
17	16.03	2987		
18	7.47	2995		
19	3.20	2998		
20	1.24	2999		
21	0.43	3000		
22				
23				
24				
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Table E.2.4 Policy 3 and 1b and combined policy

E.3 Detailed description scenarios supporting data

	IM Baserun initial		IM Baserun initial scenario1	
t	AR	A	AR	A
0	0.00	500	0.00	500
1	19.16	519	11.01	511
2	34.82	554	21.49	532
3	42.51	596	22.91	555
4	56.36	653	23.70	579
5	73.86	727	24.48	604
6	92.21	819	24.93	629
7	105.66	925	25.18	654
8	115.99	1041	25.34	679
9	128.05	1169	26.42	705
10	140.40	1309	39.50	745
11	161.73	1471	43.45	788
12	176.23	1647	51.61	840
13	182.44	1829	61.49	902
14	184.26	2014	73.36	975
15	177.53	2191	83.02	1058
16	169.85	2361	94.74	1153
17	158.51	2520	107.19	1260
18	134.22	2654	121.69	1382
19	106.25	2760	134.51	1516
20	79.92	2840	140.45	1656
21	57.30	2897	143.01	1799
22	38.91	2936	141.57	1941
23	25.34	2961	136.95	2078
24	15.96	2977	130.24	2208
25	9.73	2987	129.13	2337
26	5.75	2993	125.53	2463
27	3.29	2996	112.76	2576
28	1.81	2998	95.90	2672
29	0.97	2999	78.60	2750
30			62.95	2813

Table E.3.1 Baserun and Scenario1

	IM Baserun initial scenario2		IM Baserun initial scenario3	
t	AR	A	AR	A
0	0.00	500	0.00	500
1	19.63	520	29.87	530
2	36.11	556	54.36	584
3	45.64	601	77.08	661
4	63.94	665	127.09	788
5	89.86	755	200.68	989
6	120.87	876	264.27	1253
7	141.47	1018	312.91	1566
8	159.97	1177	333.62	1900
9	179.97	1357	318.32	2218
10	199.23	1557	291.53	2510
11	221.76	1778	240.73	2750
12	230.41	2009	142.92	2893
13	223.50	2232	69.56	2963
14	222.20	2455	27.14	2990
15	197.39	2652	7.99	2998
16	144.45	2796	1.68	3000
17	93.94	2890	0.23	3000
18	55.41	2946		
19	29.67	2975		
20	14.40	2990		
21	6.34	2996		
22	2.51	2999		
23	0.91	3000		
24				
25				
26				
27				
28				
29				
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Table E.3.2 Scenario 2 and Scenario 3

	IM Baserun initial scenario4		IM Baserun initial scenario5	
t	AR	A	AR	A
0	0	500	0	500
1	39.33	539	11.01	511
2	68.94	608	21.49	532
3	95.08	703	22.91	555
4	148.75	852	23.70	579
5	212.52	1065	24.48	604
6	276.11	1341	24.93	629
7	325.70	1666	25.18	654
8	321.02	1987	25.34	679
9	287.45	2275	29.69	709
10	248.23	2523	86.25	795
11	193.98	2717	120.37	915
12	129.51	2847	183.31	1099
13	78.41	2925	245.69	1344
14	42.78	2968	323.26	1668
15	20.22	2988	375.66	2043
16	8.17	2996	355.85	2399
17	2.77	2999	331.12	2730
18	0.80	3000	177.89	2908
19			70.64	2979
20			17.95	2997
21			2.97	3000
22			0.30	3000
23				
24				
25				
26				
27				
28				
29				
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Table E.3.3 Scenario 4 and Scenario 5

	IM Baserun initial scenario6		IM Baserun initial scenario7	
t	AR	A	AR	A
0	0	500	0	500
1	25.73	526	40.74	541
2	48.84	575	72.88	614
3	71.39	646	102.32	716
4	123.79	770	166.30	882
5	216.60	986	244.52	1127
6	300.15	1286	323.66	1450
7	368.26	1655	368.31	1819
8	403.37	2058	344.69	2163
9	380.59	2439	295.04	2458
10	341.11	2780	228.04	2686
11	170.61	2950	153.68	2840
12	45.39	2996	88.79	2929
13	4.25	3000	43.85	2973
14	0.08	3000	18.61	2991
15			6.42	2998
16			1.74	3000
17			0.35	3000
18				
19				
20				
21				
22				
23				
24				
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26				
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Table E.3.4 Scenario 6 and Scenario 7