Chapter XV

Data Mining in Health Care Applications

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ABSTRACT

Recent attention has turned to the healthcare industry and its use of voluntary community health information network (CHIN) models for e-health and care delivery. This chapter suggests that competition, economic dimensions, political issues, and a group of enablers are the primary determinants of implementation success. Most critical to these implementations is the issue of data management and utilization. Thus, health care organizations are finding value as well as strategic applications to mining patient data, in general, and community data, in particular. While significant gains can be obtained and have been noted at the organizational level of analysis, much attention has been given to the individual, where the focal points have centered on privacy and security of patient data. While the privacy debate is a salient issue, data mining (DM) offers broader community-based gains that enable and improve health care forecasting, analyses, and visualization.

INTRODUCTION

In this chapter, we provide general insight into data mining with emphasis on the health care industry. Our discussion focuses on earlier electronic commerce health care initiatives, namely community health information networks (CHINs) in three regions of the United States. From our exploration of the implementation issues that impacted the success of each case, we offer Figure 1 to illustrate a cluster of factors that capture the dynamics of these live scenarios.

While our prior work (Payton & Ginzberg, 2001) focused on the information technology implementation process, here we provide insight regarding the mining of
health data centered about new e-health models of care delivery. One such model for health care was the CHIN, which was a widely sought after model in the late 1990s, and continues to be widely debated by leading industry groups, such as The Healthy Cities Organization (http://www.healthycities.org) and the IEEE-USA Medical Technology and Policy Committee (http://www.ieeeusa.org/committees/MTPC).

While CHINs were said to enable multiple organizations to share health services data in order to meet common objective(s), ranging from profit maximization to improvement of public health conditions and wellness, health care organizations are now deploying e-health strategies to accomplish these goals while garnering data to address community and public health needs. Thus, health care organizations are finding value as well as strategic applications to mining patient data, in general, and community data, in particular. While significant gains can be obtained and have been noted at the organizational level of analysis, much attention has been given to the individual where the focal points have centered about privacy and security of patient data. While the privacy debate is a salient issue, data mining offers broader community-based gains that enable and improve health care forecasting, analyses, and visualization.

Thus, the objectives of this chapter are:
1) To describe the uses of data-mining techniques in health care;
2) To explore the intersection of data mining in the context of CHINs;
3) To explain how the CHIN platform can be used for fraud detection, profitability analysis, patient profiling, and retention management;
4) To discuss emerging and future trends; and
5) To explore the technical and social issues that remain.

DATA MINING IN HEALTH CARE

Data mining has often been defined as a “process of extracting previously unknown, valid and actionable information from large databases and then using the information to make critical business decisions” (Cabena, Hadjinian, Stadler, Verhees, & Zanasi, 1998). This definition is based on the premise that an organization can link its myriad sources of data into a data warehouse (to potentially include data marts). Further, these data sources can evolve to a higher degree of analyses to include exploration using on-line analytical processing (OLAP), statistical analyses, and querying. One mechanism that can be used to migrate beyond exploration and permit organizations to engage in information discovery is the Sample, Explore, Modify, Model and Assess (SEmma) Methodology, as developed by the SAS Corporation (http://www.sas.com). In sum, SEMMA enables its users to: 1) test a segment of data (test data) to be mined for preliminary outcomes; 2) assess this sample data for outliers, trends, etc.; 3) revise the sample data set for model testing, which can include neutral networks, linear regression, and decision trees; 4) evaluate the model for accuracy; and 5) validate the model using the complete data set (Groth, 1998).

In general, the rationale for mining data is a function of organizational needs and type of firm’s role in the industry. Moreover, researchers (Hirji, 2001; Keim, 2001) have established that data-mining applications, when implemented effectively, can result in strategic planning and competitive advantage. In an effort to minimize the collection and
storage of useless and vast amounts of data, mining can identify and monitor which data are most critical to an organization—thereby providing efficient collection, storage, and exploration of data (Keim, 2001). The efficiencies associated with mining of “most vital data” can result in improved business intelligence, heightened awareness of often overlooked relationships in data, and discovery of patterns and rules among data elements (Hirji, 2001). Others (http://www.sas.com; Groth, 1998) offer that data mining permits improved precision when executing:

- Fraud Detection and Abuse;
- Profitability Analysis;
- Customer (Patient) Profiling; and
- Retention Management.

In particular, data mining offers the health care industry the capabilities to tackle imminent challenges germane to its domain. Among them being:

- Fraud Detection and Abuse – identification of potential fraud and/or abuse; this is applicable to insurance claims processing, verification and payment
- Profitability Analysis – determination of categories of profit and loss levels; this can be practical for analyses of diagnosis related groups (DRGs) and managed care enrollments
- Patient Profiling – discovery of patients’ health and lifestyle histories as they can impact medical coverage and service utilization
- Retention Management – identification of loyal patients and services they use; as well as those patients that depart from a particular insurance group, community and profile segment

COMMUNITY HEALTH INFORMATION NETWORKS (CHINS)

During the late 1990s and again more recently, CHINs were seen to offer the health care industry a platform to address and mine medical data to support public and rural health issues. CHINs have been defined as: “Interorganizational systems (IOSs) using information technology(ies) and telecommunications to store, transmit, and transform clinical and financial information. This information can be shared among cooperative and competitive participants, such as payors, hospitals, alternative delivery systems, clinics, physicians, and home health agencies” (Brennan, Schneider & Tornquist, 1997; Payton & Ginzberg, 2001). IOSs have emerged as a primary business model in a number of industries given the application of wireless, application-integration, Internet, and broadband technologies. Starting with reservation systems in the airline industry (e.g., the SABRE system), IOSs have been used to implement strategic and competitive advantage in the cotton, hospital supply, consumer goods retailing, and automotive industries, among others (Clemons & Row, 1993; Copeland & McKenney, 1988). Given their intended direction for extensive mining of medical data among health care providers,
payors, employers, and research institutions, CHINs offer an immediate platform for patient profiling, fraud detection, profitability analysis, and retention management.

Based on a voluntary model of organizational participation, CHINs enable member organizations to share health services data in order to meet common objective(s), ranging from profit maximization to improvement of public health conditions and wellness. Further, CHINs can provide a myriad of services from electronic transaction processing to telephone-based referral information (Brennan et al., 1997). The deployment of CHINs is confronted with a tremendous number of implementation barriers, largely behavioral and political in nature. Among the numerous deterrents, as found in Payton and Ginzberg (2001), were loss of organizational autonomy and control; lack of vendor and patient support; and lack of understanding of customers’ (patients) needs. Critical to e-health models, however, are the data quality issues that enable health care providers, researchers, payors, and consumers to make more informed medical decisions.

Cooper and Zmud (1990) adopted a diffusion process model of IT implementation that is based on stages and processes as outlined in Table 1. Cooper and Zmud suggest that the process model can be used as a framework for understanding how critical implementation factors evolve over time.

Cooper and Zmud (1990) identify five broad contextual factors that might impact the implementation process: user, organization, task, technology, and environment. Their description of the implementation process, however, suggests an alternative clustering of contextual variables. For instance, they state that, in the initiation stage, “pressure to change evolves from either organizational need (pull) technological innovation (push)"

<table>
<thead>
<tr>
<th>Stages</th>
<th>Process</th>
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<tbody>
<tr>
<td>Initiation</td>
<td>Active and/or passive scanning of organizational problems/opportunities and IT solutions are undertaken. Pressure to change evolves from either organizational need (pull), technological innovation (push), or both.</td>
</tr>
<tr>
<td>Adoption</td>
<td>Rational and political negotiations ensue to get organizational backing for implementation of IT applications.</td>
</tr>
<tr>
<td>Adaptation</td>
<td>The IT application is developed, installed, and maintained. Organizational procedures are revised and developed. Organizational members are trained both in the new procedures and in the IT application.</td>
</tr>
<tr>
<td>Acceptance</td>
<td>Organizational members are induced to commit to IT application usage.</td>
</tr>
<tr>
<td>Routinization</td>
<td>Usage of the IT application is encouraged as a normal activity.</td>
</tr>
<tr>
<td>Infusion</td>
<td>Increased organizational effectiveness is obtained by using the IT application in a more comprehensive and integrated manner to support higher level aspects of organizational work.</td>
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</table>

Table 1: IT Implementation Process Model from Cooper and Zmud (1990).
or both” (p. 124). In the adoption stage, they describe the processes of “rational and political” negotiations, and in subsequent stages, they suggest that “technology” impacts the system implementation. Following this, three factor classes are defined: push/pull factors, behavioral factors and shared systems topologies. That is, these sets of factors continue to be important as organizations are pressured to change, examine opportunities for IOS solutions, obtain organizational backing, develop the IOS applications, and continue to engage in cooperative IOS arrangements.

Our proposed CHIN implementation model is shown in Figure 1. This implementation model is important to academicians and practitioners, alike – as it holds implications for data utilization, management, and mining.

Push or pull factors are contextual elements that can impact and influence an organization’s willingness to participate in IOS initiatives and include perceived competitive advantage (Grover, 1993), competition (Johnston & Vitale, 1988; Copeland & McKenney, 1988; Grover, 1993), government actions and policies (Linder, 1992; Anderson, Aydin & Jay, 1994), and perceived economic benefits (Moritz, 1986).

Among the Push/Pull Factors, we expected both the economic dimensions and government policies to have a positive impact on the implementation effort. Health care organizations are currently being pressed toward greater cooperation by government decisions, policies, and practices (e.g., Medicare, Medicaid, Joint Commission on Accreditation of Healthcare Organizations, prospective payment system). Further, the need to reduce costs while maintaining or increasing quality is a key objective of numerous managed care models (Ferrat, Lederer, Hall, & Krella, 1996; ; Grover, 1993;
Competition among institutions was expected to play a minor role, given the rise of community models of health care delivery (Brennan et al., 1997; Payton, Brennan, & Ginzberg, 1995), as health care players learn to cooperate and collaborate (Ferret, et al., 1996) in an effort to overcome the limitations associated with previously noted economic dimensions.

Behavioral factors relate to attributes and actions of key system stakeholders. These include customer support (in this study, the customer is defined as the patient); end-user support (Anderson, et al., 1994); organizational autonomy and control (Moritz, 1986); physician, application vendor, and top management support (Anderson, et al., 1994; Grover, 1993; Lucas, Ginzberg, & Schultz, 1988). In the case of CHINs, application vendor support is vital for organizations to gain access to the needed products (Kim & Michelman, 1990). Another critical behavioral factor is the political dynamics of the implementation process, which often impacts system endorsement and resource commitment (Aydin & Rice, 1992; Kimberly & Evanisko, 1981).

Of the Behavioral Factors, quality of CHIN management, vendor support, patient support, physician support, and end-user support are all expected to have positive impact on implementation progress. Each of these factors has been shown to foster change in various intra- and inter-organizational domains (Anderson, et al., 1994; Clemons & Row, 1993; Grover, 1993; Lucas, et al., 1990; Whang, 1992), and the same result should obtain in the CHIN context. Strong autonomy and control of member organizations, however, will tend to inhibit successful CHIN implementation, as organizations struggle with the tradeoffs of losing some autonomy to the benefits of shared information (Brockhoff & Teichert, 1995). Political factors, arising from conflicting personal and organizational objectives among stakeholders, will tend to impede implementation progress (Beath, 1991; Linder, 1992).

Shared or integrated systems topologies represent certain aspects of the infrastructure needed for a CHIN. These factors include arrangements for cooperation and information sharing, as well as for assuring information quality (Clemons & Row, 1993; Kim & Michelman, 1990; Mason, 1991). These cooperative arrangements for CHINs may involve physicians, hospitals, third-party payors, laboratories, and pharmacies and will require an increased degree of electronic information sharing with anticipated improved information quality (Ernst & Young, 1994; Little, 1994).

Both elements of Shared System Topologies—information sharing and information quality—were predicted to have favorable impacts on implementation progress. The prior existence of shared systems would provide foundations for building more efficient and effective mechanisms for inter-organizational, community-based health care delivery. As the degree of information sharing among inter-organizational participants increased, the quality of information available was also expected to increase, thereby fostering successful implementation (Clemons & Row, 1993).

**FINDINGS USING A CASE METHODOLOGY**

Thus, using a case methodology to test the absence or presence of the factors listed in Figure 1, the results indicated in Table 2 emerged, based on data collected from 30
interviews, organizational documentation, participant observation and application demon-
stration.

In-depth case data was collected from three voluntary CHIN implementations: the
Wisconsin Health Information Network (WHIN), Regional Health Information Network
of Northeast Ohio (RHINNO) and Northeast Ohio Health Network (NEOHN). The
parallels among these CHINs make them appropriate for investigation. Each CHIN is
located in the Midwest USA; they cover the range from big city to rural areas, and share
common initial objectives – i.e., sharing services among multiple health care players with
the potential to increase profits. In addition, each of these CHINs is thought to have
technology similarities with regard to data repositories, dedicated telecommunications
media to enable interorganizational information sharing, and the IS expertise of a single
vendor for technical, sales and marketing support. Thus, this sample of three CHINs is
a starting point to uncover patterns in the CHIN/IOS implementation process which can
later be studied in a broader sample.

The results demonstrate that WHIN, NEOHN, and RHINNO represent CHINs that
have met with different degrees of success. Both NEOHN and RHINNO have experienced
cycles of interest, investment, and development, but no sustained operation as CHINs.

Table 2: Summary of findings across cases.

<table>
<thead>
<tr>
<th></th>
<th>WHIN</th>
<th>RHINNO</th>
<th>NEOHN</th>
<th>Expected Impact</th>
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<tbody>
<tr>
<td><strong>Push/Pull Factors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Government</td>
<td>No impact</td>
<td>Negative impact</td>
<td>No impact</td>
<td>+</td>
</tr>
<tr>
<td>Competition</td>
<td>No impact</td>
<td>Negative impact</td>
<td>Negative impact</td>
<td>None</td>
</tr>
<tr>
<td>Economic factors</td>
<td>Positive &amp; negative impacts</td>
<td>Negative impact</td>
<td>Negative impact</td>
<td>+</td>
</tr>
<tr>
<td><strong>Behavioral Factors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top management support</td>
<td>Positive impact</td>
<td>Positive impact</td>
<td>Positive impact</td>
<td>+</td>
</tr>
<tr>
<td>Vendor support</td>
<td>Positive impact</td>
<td>Positive impact</td>
<td>Positive impact</td>
<td>+</td>
</tr>
<tr>
<td>Patient support</td>
<td>No impact</td>
<td>No impact</td>
<td>No impact</td>
<td>+</td>
</tr>
<tr>
<td>Physician support</td>
<td>Positive impact</td>
<td>Positive impact</td>
<td>Positive impact</td>
<td>+</td>
</tr>
<tr>
<td>End-user support</td>
<td>Positive impact</td>
<td>Positive impact</td>
<td>Positive impact</td>
<td>+</td>
</tr>
<tr>
<td>Organizational autonomy &amp; control</td>
<td>No clear impact</td>
<td>Negative impact</td>
<td>Negative impact</td>
<td>-</td>
</tr>
<tr>
<td>Political issues</td>
<td>Negative impact</td>
<td>Negative impact</td>
<td>Negative impact</td>
<td>-</td>
</tr>
<tr>
<td><strong>Shared System Topologies</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information sharing</td>
<td>Positive impact</td>
<td>No impact</td>
<td>Potentially positive impact</td>
<td>+</td>
</tr>
<tr>
<td>Information quality</td>
<td>No evidence</td>
<td>Uncertain impact</td>
<td>Potentially positive impact</td>
<td>+</td>
</tr>
<tr>
<td><strong>IOS Enablers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Systems planning</td>
<td>No information – not assessed</td>
<td>Positive impact, if present</td>
<td>Positive impact, if present</td>
<td>Not in original model</td>
</tr>
<tr>
<td>Needs assessment</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Organizational readiness</td>
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<tr>
<td>Expected Impact</td>
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On the other hand, WHIN serves as both an application (CHIN) vendor and an IOS venture electronically supporting its multiple health care participants. What differentiates these situations, and what implications can we draw from this for our model of IOS implementation?

Perhaps the biggest difference in the study results between WHIN on the one hand and RHINNO and NEOHN on the other, is the apparent impact of Push/Pull Factors. While these factors showed little impact in the WHIN case, they had a largely negative impact for both RHINNO and NEOHN implementation. These factors are, no doubt, related to the environment. The nature of the market, geographical location, and infrastructure supporting CHIN implementation differentiates WHIN from the other two cases. The Wisconsin market is characterized by a fairly large group of relatively small, non-competing health care providers. CHIN implementation in this environment is not a zero-sum game. CHIN participants stand to lose little by engaging in cooperative information exchange processes. WHIN participants, unlike those in RHINNO and NEOHN, do not appear to endorse the idea that one organization’s gain is another’s loss. Further, CHIN participation becomes particularly appealing as smaller organizations recognize their inability to fund such massive infrastructures on their own, and larger, free-standing hospitals and payors realize their limited ability to finance the expenditures associated with implementation. WHIN and its participants are located in a smaller urban environment (unlike CHIN initiatives in New York, Chicago, and Cleveland), where health care players tend to be geographically dispersed. This, in part, engenders the need to electronically share information and may explain the lack of concern for competitive forces in the WHIN case.

Figure 2 shows how the nature of the competitive environment might impact the desirability of shared IOS, including CHINs. In a large, urban market with many competing health care providers and/or payment plans, a highly competitive market develops (Box 1 of Figure 2). Institutions within this market are generally technologically sophisticated and often have their own, internal health care information systems and procedures in place to enable electronic data sharing. The nature of such markets could hinder CHIN implementations. Organizations in these competitive markets are likely to be unwilling to share information due to the perceived threat of competition. Consequently, there appears to be little justification for interorganizational cooperation or a voluntary CHIN in such markets. The Cleveland metropolitan market has these characteristics, and this may explain the failure of RHINNO to develop.

At the other extreme, small cities or rural areas with relatively few, geographically dispersed health care providers and payors present non-competitive markets (Box 4 of Figure 2). CHIN participation is most attractive in these cases, as organizations can engage in information sharing with little or no perceived threat of competition. The lack of service redundancy in the marketplace increases the likelihood that information sharing utilizing a shared infrastructure can add value. Markets in larger, less populous states are examples that fit this model. In such markets, push/pull factors like competition and economics as identified in the proposed CHIN implementation model (Figure 1) would likely favor implementation.

Boxes 2 and 3 represent moderately competitive markets, which can develop both in large and small metropolitan regions. These settings fall somewhere between the extremes of those markets characterized by Box 1 or 4. They are likely to be smaller markets, or markets with less “density” of medical providers and payors. These are likely
These different market situations suggest the need for alternative models, both for CHIN functioning and for CHIN implementation. Health care players in highly competitive environments may participate in IOS educational, general organizational information, and clinical services. Similar to trade associations, such health care cooperatives could pool resources to gain power through political lobbying, engage in knowledge transfer particularly in specialized domains, and seek purchase discounts for needed technologies and services. Widespread sharing of patient information, however, will not occur easily in such markets, as powerful players develop proprietary systems to serve their own needs and maximize their individual market shares. In less competitive markets, the true potential of CHIN functionality for sharing data among multiple providers is more likely to be realized.

As is evident from this study, the factors affecting CHIN implementation are likely to differ in different market situations. While Behavioral Factors seemed to play similar roles in each case, Push/Pull Factors and Shared System Topology (infrastructure) factors did not. The conditions for success depicted in the research model appear to be unattainable in certain environmental scenarios. This is particularly the case in environments characterized as a highly competitive. In these cases, the competitive forces,
economic justification, political issues, and IOS enablers are most critical to determining implementation success – they emerged as the go/no-go factors in the research model. Thus, it appears that the market for cooperative CHINs may be limited.

**HOW THE PLATFORM CAN BE USED**

CHIN technology would enable health care constituents to electronically create, maintain, and transform medical data via internal organizational and network-wide databases. Medical information can be housed in several tables, such as patient info, employer info, dependent info, medical records, physician info, etc. Attributes describing each entity with appropriate relationships would be established. These databases can, then, feed into a data warehouse with data marts for each CHIN constituent. These data marts can be used to manage specialized processing by individual CHIN organization. Data from the CHIN overarching database is extractable to facilitate data-mining processes.

Data mining often follows one of several methods:

1) Predictive modeling — includes classification and regression techniques that are used to forecast unknown outcomes or variables;
2) Clustering – establishes clusters (based on an analogous statistic) in order to compare historical data to analyze new data;
3) Association – determines relationships between attributes in a database that often can be correlated as a result of causality; and
4) Summarization – generalizes task-specific data into a data cube that can create graphical representations.

While several organizations (IBM, Oracle, Silicon Graphics, Angoss, SAS, and SPSS) offer data-mining technologies, the SAS Enterprise model is provided, herein, to show the technology interface (Figure 3). The SAS system supports a myriad of mining models, including decision trees, regression, and neutral networks.

Once mined, the data offers its owners knowledge regarding fraud, profiling, retention, and profit analyses. In general, these methods provide organizations using on-line analytical processing (OLAP) with a multidimensional, logical view of critical data. Thus, strategic knowledge can be derived using forecasting, trend analyses, and statistical analyses. For health care organizations, in particular, data-mining solutions can provide payors, hospitals, alternative delivery systems, clinics, physicians, and home health agencies with more succinct, meaningful answers to issues, such as:

1) (In)effective methods of patient care;
2) Local and regional health statistics;
3) Cost analyses by segments of a population, provider plan, or demographic group;
4) Drug subscription, treatment, utilization, etc.;
5) Genetic treatment, medical research, and discovery; and
6) (In)effective methods for mining “text-based” clinical data.

As Figure 2 suggested, regional markets in Boxes 1 and 4 are best suited for these implementations. Moreover, Box 1 (Highly Competitive Medical Markets) is likely to
serve as an ideal environment given the presence of larger number of payor plans and enrollees – thereby resting on the notion that CHIN participants are in need of vital data analyses on cost effectiveness, profitability, treatment, resource utilization, etc. In noncompetitive environments (Box 4), the health information network fosters a coupling on dispersed groups where competition and economic dimensions are not the primary drivers of the implementation.

To this end, CHIN technologies offer the industry the ability to better mine larger sets of data to accomplish four critical analyses:

1) Fraud Detection – Of particular interest to health care providers, this application features provider and patient profiling along with behavior and resource utilization, charting tools, and detection functionality. To this end, data mining via CHIN technologies permits continuous monitoring on the above, yet these analyses are performed on a broader scale (i.e., local, state, and regional levels). Moreover, similar to fraud detection among credit card agencies, CHIN constituents, particularly government agencies, can mine data to discover (mis)uses of medical benefits, monetary losses, and legal infractions.

2) Profitability Analysis – Figure 1 and the material that follows clearly points out the criticality of the implementation process. As noted in Table 2, every CHIN
participant organization was significantly concerned about the economic dimensions associated with investing in the network technologies in question. While the CHIN technology enables larger data sets to analyzed, its users can conduct additional regional analyses by metropolitan areas, counties, states, and districts. Effective health care plans, services, care delivery plans, and even those “profit generating” physicians - can be determined. Ineffective or non-profitable services can then be eliminated based on the more global analyses generated from data-mining technologies.

3) Patient Profiling – By using psychographic data, CHIN research members can gain amore extensive examination of patient behavior to uncover treatment and care service utilization patterns. For example, mined data could profile patients by physicians visited and medical tests ordered, drug treatment, gender, ethnicity, age, episode of illnesses, just to name a few.

4) Retention Management – Customer relationship management is linked to the notion of retention management. Ideally, health care payors would like to retain their existing customer bases while attracting and converting potential customers to enrollees. Data mining via the CHIN facilitates cross-selling and electronic marketing services. While the case can be made for preserving patient members, health care groups must also think in terms of “retaining” physician members as well. Thus, identifying services critical to participating physician groups can be just as fundamental.

DATA-MINING IMPLICATIONS:
CONTROVERSIES AND ISSUES ASSOCIATED WITH CHINS

A close examination of Table 2 suggests the primary determinants in attaining a successful CHIN implementation are overcoming Competition, Economic, Organizational Autonomy and Control and Political Issues – thereby indicating that the technical or technology implementation is not the deterrent. Rather, the above issues relate to the broader social and political dynamics of the health care industry. Of the thirty interviews with members of these projects, there was consistent concern about two issues: 1) what is the purpose of warehousing community data?, and 2) how should the data be used?

To address the first question, numerous writings have offered rationale for warehousing health care data. For instance, the 2001 American Medical Informatics Association Conference (http://www.amia.org) hosted several panels and paper sessions to address the needs of warehousing medical data; these assessments included:

1) the critical integration of clinical and administrative data from a myriad of source systems;
2) determination of cost efficiency measures between the general population and individual patient; and
3) retrospective and prospective studies of medical history, prescriptions and laboratory results among patient medical records.
The warehousing of patient data, particularly in a CHIN domain, offers the industry the capability to more efficiently identify risk factors associated with disease episodes and prevention-focused public health requirements, and to electronically link the diverse players (e.g., providers and payors – insurance companies) along the health care continuum. Moreover, such applications lend themselves to intelligent data analysis that require accurate data quality technologies in the mining of health care data.

To determine how warehoused health care data can be best utilized, one can return to the outcomes of the CHIN cases. One recurring theme from each of the cases was the need to access data for resource utilization and determination of medical outcomes within a broader population, in general, and single patient, in particular. Other uses of these data include pattern identification by sample groups by statistically slicing the data by demographic, socio-economic and other characteristics. All of these uses of warehoused health care data stimulate more effective and efficient deployment resources and knowledge bases among communities - thereby influencing public policy implications.

While data-mining applications offer the industry these and other advantages, the social challenges abound. The erosion of personal privacy and the security of the data remain formidable issues. These are particularly of issue regarding existing health care Web sites (e.g., http://www.webmd.com, http://www.mayoclinic.com) that enable consumers to track data (e.g., on AIDS/HIV, diabetes, cancer, sickle cell anemia, etc.) and can provide marketing and medical leads for drug manufacturers and health care insurers. According to the Association of Computing Machinery (ACM) U.S. Public Policy Committee (http://www.acm.org/usacm) and other industry groups, horror stories about unauthorized disclosure of patient information are numerous; consumers continue to battle the losses and costs associated with privacy invasion. As pointed out by Barbara Simons, chair of the ACM Public Policy Committee, (http://www.acm.org/usacm/privacy/simons_medical.html ) drafts from the National Information Infrastructure Task Force stated:

“medical information is routinely shared with and viewed by third parties who are not involved in patient care. The American Medical Records Association has identified twelve categories of information seekers outside the health care industry who have access to health care files, including employers, government agencies, credit bureaus, insures, educational institutions and the media.”

Further, and in the context of data mining and CHINs, several questions remain unanswered with regard to the warehousing and mining of health care information:
1) Who owns the data?
2) What are the costs associated with the “inability” to mine community data?
3) What security policies and procedures should be implemented in a CHIN (data-mining) application?
4) How do CHINs improve public health?
5) How should organizational practices be re-engineered to ensure that security policies and procedures are practiced within the organization?
CONCLUSION

The proposed IOS implementation model derived from Cooper and Zmud’s (1990) single organization model is able to capture some aspects of CHIN implementation. The model, however, seems best suited to less competitive market situations where there is recognition that competition does not necessarily preclude interorganizational cooperation. Further, our results suggest that competition is the overriding factor in the model, thereby implying that not all variables in the model are equally important. Health care organizations in some more competitive markets have yet to rationalize the web of players (e.g., physicians and production workers, payors, providers, patients, government, and larger external environment) that directly affect its (in)ability to form cooperative ventures. The case data indicate that large health care providers and payors in some markets are evolving toward less cooperative, more coercive IOS strategies. These organizations mandate IT direction, infrastructure support, and the degree to which competitors will form cooperatives. This is evident in emerging health care organizations, such as Healtheon/WebMD and CyberCare.

These results, while interesting, must be viewed as preliminary. This was an exploratory study and was limited to CHINs located in the Midwest. CHINs implemented in what the industry considers more advanced health care states, such as Oregon, Minnesota and California, are characterized by a high degree of managed care and competition, and potentially can be impacted by a different set of conditions. Thus, another implementation model or subset of the current model may be more appropriate, and these results may not be applicable in more mature health care markets. Moreover, these early CHIN efforts speak to the challenges the industry faces as we enter the age of electronic commerce models that stand to debunk archaic views of care delivery, patient as primary consumers, information privacy, and data management.

ENDNOTE


REFERENCES


