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Antecedents and Catalysts for Developing a Healthcare Analytic Capability

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Abstract:

Analytics is the most advanced component of business intelligence. An analytic capability enables fact-based decisions using quantitative models. These models draw on statistical and quantitative analysis of large data repositories. An analytic capability is especially critical in healthcare because lives are at stake and there is intense pressure to reduce costs and improve efficiency. This study proposes antecedents and catalysts for developing an analytic capability based on an in-depth study of the cardiac surgical programs of the Veterans Health Administration (VHA). The VHA has developed an analytic capability for patient treatment and administrative decision-making. The models rely on the input of clinical data from multiple facilities. However, a diversity of standards, infrastructure, staff and patient mix result in misunderstood data definitions, errors in data entry, incomplete data sets, and conflicts between multiple systems. Consequently, data aggregation and data interoperability at both the systemic and semantic levels are challenging. Catalysts for developing an analytic capability, derived from the VHA case study, include a community of practice and patient case reassessment practices. Antecedents of an analytic capability include robust data aggregation and cleaning practices and establishment of data standards followed by judicious tailoring of analytic outputs to decision making needs.

Keywords: healthcare Information Systems, business analytics, Electronic Medical Records, data interoperability, community of practice

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I. INTRODUCTION

With the U.S. healthcare industry under extreme pressure to reduce escalating costs [Catlin, 2006], the use of Information Systems that can support key healthcare processes is particularly important as a means of increasing the efficiency and quality of care [Raghupathi and Tan, 2008]. Moreover, the rapid growth in clinical data repositories from increased use of EMR (Electronic Medical Record) systems in patient care facilities has motivated Business Intelligence (BI) in healthcare to facilitate decision-making and improve healthcare processes. Business Intelligence systems "combine data gathering, data storage, and knowledge management with analytical tools to present complex internal and competitive information to planners and decision makers" [Negash, 2004, page 178]. The most advanced component of a business intelligence capability for decision-making is analytics. An analytic capability drives decisions and actions by extensive use of data, statistical, and quantitative analysis, explanatory and predictive models, and fact-based management [Davenport and Harris, 2007]. Predictive modeling could enable early detection of high risk patients for interventions, while more advanced prescriptive analytics using optimization could generate clinical recommendations [Adams et al., 2010].

Such decision-making scenarios depend on the creation of models that draw on aggregated healthcare data in large repositories [Raghupathi, 2011]. While large health-related datasets now exist, analytic capabilities are a challenge because of a lack of complete, accessible, and useable data [Adams et al., 2010; Bloomrosen and Detmer, 2010; Stead and Lin, 2009]. Moreover, data aggregation is problematic because of (1) the varying degree of data reliability, (2) dynamic heterogeneous data from specialized medical practice, (3) a lack of technical standards, and (4) collaborative discussions that are not captured or supported by computer technology [Adams et al., 2010; Stead and Lin, 2009; Wright et al., 2009]. Key functions in a typical healthcare analytic capability include data aggregation from multiple heterogeneous sources, cleaning, transformation and validation, data warehousing, model generation, and user interfaces for user-role-based access to the outputs [Ferranti et al., 2010]. Cleaning, transformation, and validation of data involve both automated and manual procedures [Chasalow, 2009]. Manual procedures are needed when the healthcare data are conflicting and consist of narratives that require interpretation. Various terms need to be harmonized during data generation, translation, dissemination, and adoption [Bloomrosen and Detmer, 2010]. Other issues include the lack of support in commercially available clinical Information Systems for integrating the analytics into clinical workflow [Wright et al., 2009]. Finally, an analytic capability needs to address varying needs for outputs from diverse stakeholders [Bloomrosen and Detmer, 2010]. In summary, analytic capabilities in healthcare usually require add-on components, such as organizational practices for data aggregation and model generation, to use patient data from the EHR system and process it to deliver knowledge to various stakeholders in the organization.

Despite the need to establish analytic capabilities for effective decision-making in healthcare, a mature approach to analyzing and leveraging resources to build the capability has yet to emerge [Ferranti et al., 2010]. Furthermore, research on organizational aspects of BI overall is sparse [Chasalow, 2009; Jourdan et al., 2008]. Consequently, there are calls for more research to understand "what works" and "promotes" the delivery of evidence-based care enabled by medical analytics [Bloomrosen and Detmer, 2010]. Nevertheless, very little research has been published on BI in the healthcare field and benefits are rarely studied [Jourdan et al., 2008].

Research Goals

This study will address this research gap, focused on analytics in healthcare. The objective of this research is to clarify the process by identifying antecedents and catalysts for developing a healthcare analytic capability. In addition, the goal is to make explicit the outcomes of this capability.

The next section discusses the research background on data warehousing, BI and analytic capability. This background is followed by the research methodology and then the VHA case study. We discuss our findings and implications, and then conclude with limitations and future research directions.

II. RESEARCH BACKGROUND

Data warehousing is the activity of transforming and storing massive volumes of data generated by organizations in an integrated data warehouse [Watson and Wixom, 2007]. In healthcare, increased use of EMR have generated large data repositories [Raghupathi, 2011; Raghupathi and Tan, 2008]. Extract, transform, and load (ETL) prepares the data for decision support [Watson and Wixom, 2007]. However, poor data quality in the heterogeneous source

systems contribute to issues requiring about 80 percent of the BI project time and effort, as well as generating more than 50 percent of the unexpected project costs. Furthermore, data quality and system quality are determinants of perceived net benefits of data warehousing [Wixom and Watson, 2001].

BI is the process of getting data out of the data warehouse [Watson and Wixom, 2007]. The BI process is also composed of methods to develop useful information for organizations [Jourdan et al., 2008]. The BI product is information to help an organization make relevant predictions. Organizations in almost every industry are increasingly using BI to make better decisions and extract value from their business processes [Davenport and Harris, 2007; Watson et al., 2002]. In healthcare, organizational processes identify needed data elements from patient care activities. For decision-making with structured data, predictive models, such as regression models, allow the creation of calculators of mortality or morbidity risk for procedures such as cardiac bypass graft (CABG) surgery. However for decision-making with unstructured data, such as blogs and textual information, classification models are used to identify patterns and create meaning [Raghupathi, 2011].

An important part of any BI implementation is how the system will be used by people to achieve organizational goals [Jourdan et al., 2008]. The characteristics of BI users and the organizations within which they work can have a disproportionate impact on the benefits derived from investments in BI [Chasalow, 2009; Shanks et al., 2010]. For example, the professional autonomy of physicians creates a culture of intuitive decision-making [Adams et al., 2010; Sherer, 2010]. This culture hinders adoption of BI by the physicians who are skeptical of the BI outputs and hesitate to use them in their practice. A reluctance to spend time away from direct patient care to record patient data into electronic health records becomes an issue for data aggregation.

An analytic capability drives fact-based management decisions and actions with extensive use of data, statistical and quantitative analysis, explanatory and predictive models [Davenport and Harris, 2007]. Success with advanced analytics is highly dependent on the quality and completeness of the data subject to analysis, as well as the sophistication of the algorithms and models on which analyses depend [Adams et al., 2010]. The availability of high quality data and technology needs to be coupled with organizational routines and individual skills for an analytic capability [Shanks et al., 2010]. A model of organizational competence for harnessing IT shows the antecedents are individual know-how and skills and purposeful heedful interactions [Chasalow, 2009; Dhillon, 2008]. Heedful interacting occurs when many individuals work together as if they were of one mind [Chasalow, 2009; Dhillon, 2008; Weick and Roberts, 1993].

However, healthcare organizations typically operate in specialized practices with minimal data/process standardization and integration. Minimal standardization and integration leads to difficulty in creating organization-wide high quality data assets [Shanks et al., 2010]. Healthcare infrastructures that lack interoperability pose a challenge to building data warehouse systems that can support an analytic capability [Hammond et al., 2010]. For example, the realization of a fully connected large UK healthcare network has been problematic [McGrath et al., 2008]. The problems include systems and semantic interoperability issues. Specifically, the meaning of the data varies by medical practice and specializations, so aggregation of data across multiple EHR systems is extremely complex.

Standards are critical for interfaced medical records from multiple medical practices and systems [Adams et al., 2010]. There are over 300 EMR or EHR vendors with systems that differ in their data fields, workflows, and medical protocols. HL7, which is an abbreviation of Health Level Seven, is a standard for exchanging information between medical applications [Gupta et al., 2007]. Although the HL7 standard defines a format for the transmission of health-related information, and other standards for healthcare information are being developed by a technical committee of the International Organization for Standardization (ISO) [Altinkemer et al., 2006], complete agreement is elusive [Raghupathi and Tan, 2008]. Consequently, exchanging medical data in the current environment is difficult.

Semantic interoperability is defined as the preservation of meaning in information and data as it moves between systems and users or is repurposed [Goodenough, 2009]. Preservation of meaning is critical for safe clinical care and for administrative decisions based on statistical analysis of healthcare data. Standards help to ensure data is semantically unambiguous [Goodenough, 2009; Hammond et al., 2010]. However, ensuring data standards are followed when building an overall health record for the patient by combining medical records is often problematic. Typically, facilities in which patient care is delivered vary widely, ranging from "basic" centers with limited scope of medical practice to highly "advanced" urban hospitals with state of the art medical technology for patient care. In a typical scenario, when patients receive care in multiple facilities and from several clinicians, there can be differences in their care protocols and workflows resulting in large variations in the medical records generated for patients.

Additionally, the diversity in medical group practices is well documented as medicine is practiced in specialties. Each specialty has its own set of laboratory datum, medical protocols, and treatment regimens. Hence, medical records

created by one specialty can be difficult to use in other practices [Gupta et al., 2007]. To build an analytic capability, a holistic assessment of a patient is needed, yet is missing in medical records that have been generated from silo-based islands of specialized care [Raghupathi and Tan, 2008]. Even after establishing standards for data definitions (semantic interoperability) and standards for integration and aggregation of data from multiple systems (systems interoperability), the dynamic and piecemeal nature of medical data creates issues with building this holistic view of the patient case [Bloomrosen and Detmer, 2010]. The overall design and implementation of these analytic techniques in healthcare can be facilitated by effective organizational practices that help to bridge the silos of specialized healthcare departments. Such an approach requires interfacing the analytic capability with existing healthcare systems and processes than spans the entire organization and supports a wide range of users—both clinical and administrative. Consequently additional "value creating actions" [Shanks et al., 2010] or "catalysts" must be instituted to build and deliver the analytic capability and derive benefits from it.

III. RESEARCH METHODOLOGY

A qualitative interpretive methodology was used to guide the research. The case study organization was the Veterans Health Administration (VHA). Our understanding of the VHA approach to building an analytic capability and deploying it across its healthcare network of cardiac surgical programs was based on interviews with clinical and administrative staff. The unit of analysis is the collection of over forty cardiac surgical programs located at different VA hospitals throughout the country. While each surgical program is hosted and mostly managed by the local VHA facility, policy making for these surgical programs is done at a nationwide level through surgical advisory boards and surgical consultants. The collection of cardiac surgical programs also undergoes multiple periodic reviews when the outcomes of each program are compared. Three clinicians, two regional administrators, and the national nurse executive along with the administrator of a community of practice were interviewed face-to-face over several weeks. A total of fifteen hours was spent in these interviews. The research background suggested a major challenge in creating a healthcare analytic capability is the aggregation of data from heterogeneous systems used to build a holistic patient health record. The interview questions aimed to understand the organizational practices that supported overcoming this challenge at the VHA. Although the interviews were open-ended, we posed the following questions to guide the theory building: (1) what types of challenges do you face in your data collection practices for CICSP? (2) what types of knowledge need to be shared? and (3) what are the systemic benefits of collecting and sharing this data? During the period of data collection, we augmented our insights by searching and analyzing the relevant literature.

Two researchers coded the information using free-form database software. Each interview was transcribed to a separate document and the documents uploaded into the tool. This tool has a sophisticated search engine and features that enable saving search terms. Output from the search results for a specific code can be generated. Analysis followed the contact-comparative method [Strauss and Corbin, 1998]. Factual coding was done on the transcripts to capture a timeline of key events in the CICSP program and descriptive information, such as program goals, priorities, and challenges about the CICSP program. In a comparative coding step, the researchers classified interview segments into themes that were previously identified in the BI and data mining literature in healthcare. Themes included typical components of an analytic capability such as data interoperability, data identification, collection and aggregation steps, and model generation. During the open coding step, the researchers identified two unanticipated additional themes. The first theme was the use of a community of practice to support data aggregation during the input stage. The second theme was the promotion of understanding and use of model outputs among the organizational stakeholders. The relationships between these themes were identified during a process of interpretation. Analysis continued until no further concepts emerged—the point at which theoretical saturation was reached.

IV. VHA CASE STUDY

This case study shows how the VHA effectively aggregated medical records from multiple care facilities to build a reliable analytic capability. This analytic capability supported the delivery of patient care and administrative decision-making. Leadership promoted metrics and performance management, and invested in the appropriate skills, infrastructure, and tools. Tools included data warehousing tools, data cleaning tools, statistical tools, content management system, and handheld devices for clinical decisionmaking.

The Continuous Improvement in Cardiac Surgery Program (CICSP) successfully implemented an analytic capability using medical records from a wide variety of VHA facilities and practices. Some were internal to the VHA network and some were external affiliate facilities. CICSP began collecting VHA-wide cardiac surgery data in 1987 [Shroyer et al., 2008]. It implemented an innovative analytic capability initiative that used historical outcomes of surgeries and procedures to develop statistical risk models. The models facilitated decisions (Table 1) on how to allocate resources and choose future treatments. The analytic capability was developed for use by (1) clinical care providers needing to assess the surgical risk for a specific patient as well as tracking outcomes, (2) hospital and regional

administrators needing outcomes data over a facility or region, and (3) VHA national administrators needing data across the entire healthcare organization.

Table 1: Decision-Making Scenarios by Organizational Role	
Role	Stakeholder Decision-Making Scenarios
Clinician	Assess the riskiness of a certain surgical procedure for a given patient based on the patient characteristics and presenting conditions
Facility Administration	Determine the resource utilization for the facility.
	Compare facilities based on outcomes.
	Determine geographic distribution of patients based on their address.
	Determine additional community based support services needed.
	Determine compliance with treatment regimens and medications.
Policy Setting (System Wide)	Assess the outcomes of policy initiatives (e.g., patient wait times).
	Determine what resources are needed to meet new legal directives.
	Develop medical protocols e.g., "Should a procedure 'X' be part of our medical care protocol?"

This CICSP analytic capability became part of VHA's ongoing transformation that new leadership began in 1995 [Venkatesh et al., 2007]. The analytic capability facilitated data-driven decision-making by providing accurate, reliable, and timely models, and quality outputs to clinical and administrative team members. The analytic capability supported their facility's surgical quality assessment and assurance activities [Kim et al., 2005] and facilitated monitoring cardiac surgical programs for quality improvement [Grover, 2008]. VHA embraced metrics and performance management and since 2000 has scored better than private healthcare organizations on multiple outcome measures [Arnst, 2006; Longman, 2005]. Measurable improvements were seen in clinical outcomes of the surgical programs over time. These improvements included decreased mortality and morbidity from surgery, shorter wait times and length of stays, greater compliance with medications, and more standardized treatments, such as the use of cardiac catheterization and combinations of medications. The success of the analytic capability also translated to better and more efficient care processes [Grover et al., 2001]. Overall costs decreased. Consequently, the cost of insuring a VHA patient was $4100/year compared to more than $6,300/year on average outside the VHA [Arnst, 2006; Kizer and Dudley, 2009].
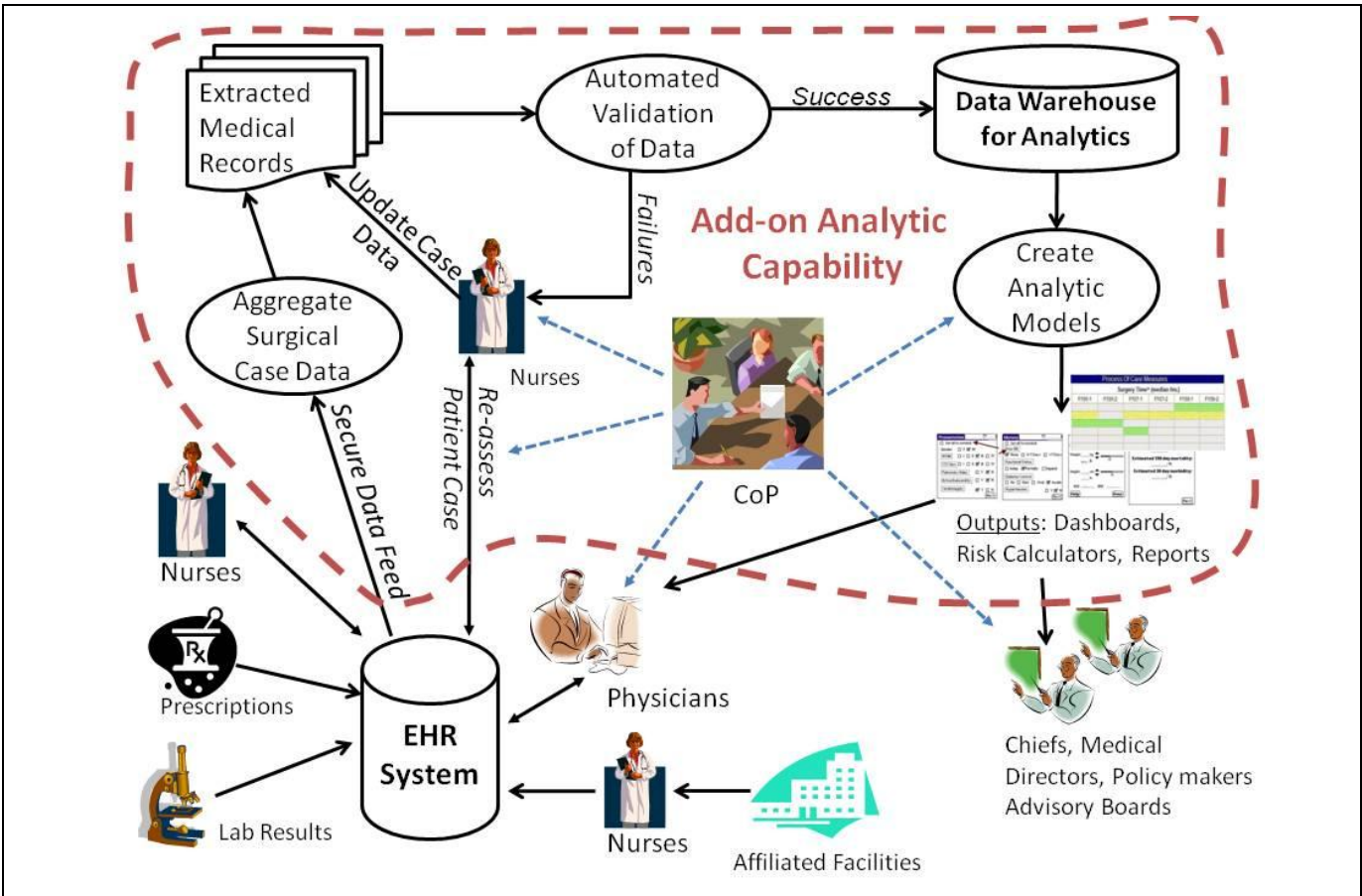
Analytic Capability Findings

The CICSP analytic capability started with extracting aggregate surgical case data from EHR systems using a secure data feed (Figure 1). The extracted medical records needed to be loaded into a data warehouse for analytics. Although the VHA's organizational complexity and the diversity in their multiple facilities posed a significant challenge, the capability provided a robust infrastructure for transmission of encrypted medical data and database servers to store, clean, and process that data. However, variations in recording standards caused issues, such as (1) incomplete patient electronic records, (2) lack of required data variables, and (3) inconsistent classification of preoperative and postoperative variable codes. The inherent diversity and dynamic nature of the medical data collected from multiple sources meant that a fully automated solution for data aggregation was not feasible. The automated procedure involved database servers that ran a battery of validation checks. Successful validation resulted in delivery to the data warehouse. Validation failures which were listed on reports as inconsistencies needed manual procedures to update patient case data. Manual procedures involved additional medical judgment. Recording nurses reassessed patient variables and conditions during follow-up visits. They manually checked new data and resolved inconsistencies. A community of practice (CoP) was critical for manual procedures and will be discussed in more detail in the next section. Our field study of the VHA cardiac programs showed resolving issues relied on both automated and manual procedures. The models generated from the analytic capability were accessible to personnel for the effective usage of system outputs in decision-making. Better decisions in the care delivery processes have resulted in multiple measures of improved patient care.

V. ANTECEDENTS AND CATALYSTS FOR AN ANALYTIC CAPABILITY

The analytic capability included a data collection, cleaning, and ETL function, a processing and model generation function, and a reporting or output function. The VHA case study enabled us to identify two antecedents and two catalysts for developing an analytic capability. The two antecedents help ensure data collection and aggregation quality by interfacing medical records from multiple facilities. The two catalysts are important for improving the analytic capability. The three outcomes of an analytic capability focus on the usage of the output. These antecedents, catalysts, and outcomes of an analytic capability are listed in Tables 2, 3, and 4 respectively.

Figure 1. Analytic Capability Add-On to EHR System

Antecedents

Antecedents are necessary conditions. The two antecedents for the CICSP analytic capability were necessary conditions for VHA to develop this capability. The first antecedent was the setup of procedures for data quality and data aggregation. The second antecedent was establishment of standard data definitions (Table 2). These two antecedents ensured interoperability of multiple EHR systems.

Table 2: Antecedents for an Analytic Capability		
Procedures for Systems Interoperability	Automated validation (see below) and manual procedures were required.	
	Automated Validation	*Example*
	Completeness of the records	All fields are present and all surgeries for the period are accounted for.
	Range of values	Systolic blood pressure between 50 and 250.
	Consistency between fields	Date of discharge is after date of admission.
	Duplication	Flag all exceptions for manual certification. Duplications and conflicts in physician's notes, lab values, and measurements like surgical time.
	Verify totals, concordance of multiple data sources	Verify total complication counts, mortality counts using clinical data and administrative (benefits) databases
Standard Data Definitions to support Semantic Interoperability	Establish practices for supporting the creation of standard data definitions and supporting those data definitions	
	Practice	*Example*
	Periodic Conferences to "Harmonize" Data Definitions	Data definitions and the way patient cases were being categorized (e.g., "Acute renal failure—yes or no") was discussed periodically to harmonize
	"The Data Bible"	The nurses consulted a "bible" of definitions constantly to check for updates.
	Annual Inter-rater Testing Case	Inter-rater reliability testing used to ensure data quality was consistent among the nurses.

Procedures for Systems Interoperability

An automated system was essential to process and correct conflicting, missing, or invalid data in medical records originating from multiple EHR systems. Automation supported each phase of medical record data entry. In the data collection phase, the clinicians used forms to make their data collection more efficient. These devices restricted data collected to ranges of values from menus and increased data quality and standardization of variables. Medical records were also collected without using templates and transmitted between medical systems using automated interfaces such as HL7. Threats to data quality identified earlier needed to be resolved in these situations (Table 2). Therefore, technology in the form of a content server, database management system, and Web portal site, restricted authorization of the appropriate nurses to use the site to view, update, and certify these medical records.

Effective data collection of patient data from several sources depended on several organizational procedures. A data quality manager monitored data concordance tests, managed database validation processes, and certified a period's data before it was loaded into the data warehouse. Data concordance tests were done between the clinical (EHR) data and administrative (benefits) databases to validate mortality totals. The data validation process included multiple checks of totals and summaries. Automated database checking needed to be done when patient medical records came into the system. Validation failures were flagged for manual certification by the data manager. A qualified clinician, typically a nurse, was responsible for the timely resolution of data checking failures. No matter how good the incoming medical records might be, without a manual checking process by a qualified clinician, there was potential for a major misunderstanding in the data set.

Establish Data Standards for Semantic Interoperability

Despite automation of some data input and the deployment of tools to support the automation of health record collection and integration, much of the patient data was entered manually in VHA's EHR system. A multitude of clinicians, such as residents, attending surgeons, department chiefs, and operating room, circulating, and medical nurses entered data. However, staff turnover, varying processes and diversity in work systems resulted in non-uniform data entry that could not be aggregated or compared. Typical problems ranged from misunderstanding data definitions, errors in data entry, incomplete data sets, conflicts between multiple data sources, and inaccessibility of data from remote facilities when patient care is brought in-house after surgery. Preservation of meaning is critical when healthcare data is aggregated from multiple systems and facilities. A team of dedicated nurses for each surgical program ensured high quality data was collected and aggregated for the analytic capability. For example, the data recording nurses abstracted some variables after consulting multiple physician notes and other fields in the patient record. The team faced multiple challenges associated with geographic dispersion of facilities and from reconciling data that originated in multiple incompatible systems, as well as in charts and scanned paper forms. Since data definitions varied across systems or facilities, the nurses consulted a "bible" of definitions constantly to check for updates. This practice helped to ensure semantic interoperability.

The nurses also used a community of practice (CoP) discussion forum for training on how to control variation in the data collection steps across multiple patient record systems. Inter-rater reliability was measured to ensure data quality was consistent among the nurses. Nurses provided intelligence in this difficult-to-automate process. Because of the limitations of automated data cleaning when complex, dynamic, and incompatible medical records were used as the source, manual processes were preserved side by side with automation to guarantee successful integration of data from multiple EHR systems (Figure 1).

Verifying data for preoperative variables was difficult. Despite the use of EHR systems, our interviews showed that paper forms had not become obsolete. Although the forms were scanned into the system, sometimes the sheets were scanned in upside down or had missing information. Unfortunately, obtaining data from a scanned sheet was a problem since the image was not a data point. The nurses had to review these data inputs and "discover" data "hidden" in charts and scanned documents.

According to interviews with recording nurses, who were involved in data collection and cleaning, it was important to extract data from CT scans, MRIs, and patient charts. Procedures varied by location according to the availability of resources. Although the VHA's EHR systems supported Web access and were widely used, many remote sites did not automate their charts. Moreover some of the local facility-specific systems were outdated and lacked a user-friendly graphical user interface. As a result, the nurses needed to check and interpret the data and used manual procedures to ensure accuracy. For example, in one legacy system, the input program did not allow two data values to be stored for the same peri-operative variable, although one data point was available from the serum test and another data point was available that was calculated. The nurse used judgment to determine what data point to input.

Catalysts

Catalyst is a term used to describe a factor that speeds up or facilitates a process. Prior research determined catalysts for the overall VHA transformation [Venkatesh et al., 2007]. In contrast, this research is focused on the analytic capability in the VHA cardiac surgery units. The following two catalysts are organizational in nature and are summarized in Table 3.

Table 3: Catalysts for an Analytic Capability		
Community of Practice	The CoP encouraged discussion of the data inputs and outputs to build understanding of procedures and interpretation of outputs.	
	Practice	*Example*
	Build common understanding of data fields	"Operative Death" is defined as within 30 days by us, 60 days by the contract facility."
	Build correct interpretation of the analytic models	"How are surgical outcomes from affiliated facilities factored into the morbidity risk model?"
Reassessments of Patient Data	This step allowed comprehensive patient assessment.	
	Task	*Example*
	Resolve conflicts between multiple data sources and multiple facilities	"Physicians are reluctant to rely on the symptoms recorded at another facility for lack of standardized evaluation charts across facilities."
	Build holistic view of patient case—abstract meaning from patient charts	"We lose information, such as why a patient is on a certain drug, if no one looks at charts."

Community of Practice

A *Community of Practice* (CoP) is loosely defined in the IS research literature as a group of individuals bound together by shared expertise with a passion for joint enterprise toward a shared goal [Wenger and Snyder, 2000]. A CoP is an example of an organizational practice that can promote the spread of best practices, develop employee skills and support knowledge sharing in the support of business goals and processes.

The VHA established a community among the users and data collectors to facilitate collaboration. Building a CoP for these nurses alleviated problems with the interoperability of data originating in multiple systems and documents. Through the participation in the community, the nurses supported each other by identifying ways to use the EHR to more effectively collect, process, and transmit data. The community facilitated semantic interoperability of the healthcare data by building and sustaining standards to ensure the data were unambiguous. Their interactions also built trust and identified norms within the team, allowing them to share knowledge more effectively and carry on data collection activities that spanned multiple facilities within the surgical program.

Collaboration was important for developing standard data definitions. Without standardization, data could not be accurately compared across multiple sources. The CoP promoted data standardization by facilitating unstructured knowledge sharing and knowledge reuse. The national executive nurse was a sponsor who supported relationship building among the CoP's members. This sponsorship was critical for ensuring quality during data collection. The community helped improve understanding of procedures, EHR integration, patient assessment, and interpretation of outputs. The CoP also encouraged adoption of the analytic capability and bridged the diversity inherent in a large organization such as the VHA.

Re-Assessment of Patient Data

Nurses at each surgical program followed surgery patients' pre and postoperative and abstracted data as patient conditions evolved and treatment was administered. For example, the nurses abstracted some variables after consulting multiple physician notes and fields in the patient record and after attending meetings and rounds. More effective patient assessment and better care resulted from collecting and interfacing medical data from multiple sources. However, cleaning and interpretation capabilities were needed to support this comprehensive solution. As medical record data transmissions were received, these records needed to be assessed and cleaned before incorporation into the data warehouse for analytics. This step allowed comprehensive patient assessment. The nurses reviewed the patient's medical data, followed up to resolve questions raised and conflicts found and built the culture for using analytics in the medical care processes. During this cleaning process, any conflicts and misunderstandings in the data needed to be resolved. Once cleaned, the data was ready for processing. The cleaning process allowed an opportunity for conducting a patient assessment as new medical evidence was received. To interpret the data correctly, collaboration among clinicians was particularly important in this step.

Despite good collaboration among nurses doing data collection at the VHA, the practice of "farming out" to contracted facilities outside the VHA created issues with interfacing information. When surgeries and care were "farmed out," internal and external nurses helped each other collect patient data from these outside facilities, reassess the patient case, and interface this data into the repository used for analytics.

Analytic Capability Outcomes

The analytic capability at the VHA enabled outcomes in the form of system outputs that were used for decision-making. These outputs needed to be aligned to the user needs. Impacts from the analytic capability were measured to show process improvements.

After collection and validation, the data were processed and information outputs were tailored to support decision-making at multiple levels of the VHA with data views based on roles of the users. Presentation of the VHA-wide information in models that provide "use-based data quality" are particularly important in the success of any analytic capability [Kim et al., 2005]. VHA system outputs included (1) a patient risk calculation model (Figure 2), (2) scheduled reports, and (3) performance dashboards (Figure 3). The physicians used PDAs and online risk calculators to access the patient risk assessment models (Figure 2). The risk model allowed the clinician to enter data about the presenting patient and then receive an estimate of the risk of mortality and morbidity after surgery.

Table 4 summarizes the outcomes of the VHA's analytic capability.

Table 4: Outcomes of the Analytic Capability	
System outputs for role-based decision-making	• Risk-adjusted models accounted for risks of any treatment due to the patient's preexisting conditions. • Statistical models integrated into the clinical protocols associated with treatment and delivery of patient care account for greater variation in patient medical conditions. • Dashboards were used in monitoring, planning, and auditing surgical programs in multiple facilities.
Integrate output into organizational processes	• Reports were used to review programs at the national board level. • Comparative rankings from the models guided the selection process into which facilities were selected for site visits and audits.
Measurement of impacts	Measure success using (1) patient-outcome based measures, such as mortality rate, morbidity rate, patient safety, and satisfaction with the care, and (2) process-based measures such as improvement in utilization, length of stay, operating room time.

System Outputs for Role-Based Decision-Making

The statistical risk models analyzed system-wide data on outcomes of treatment and adjusted for the differences in the risk of the presenting patients. A model accounted for the possibility of greater risks from treatment due to preexisting conditions of the patient. Typical risk adjustments required the building of statistical models. For example, logistic regression was applied to data from across all facilities and regions, and the resulting model was used to predict an expected value of each measured outcome for each facility's patient load. The expected value was then compared against the observed value for the measured outcome for the region or facility. This observed/expected ratio (OE ratio) was used to compare across regions or facilities. Hence in an analytic capability supporting a distributed healthcare organization, risk-adjusted measures of outcomes should be used to support decision-making.

The risk model was also available online for distribution and use by surgeons in assessing the risk of a patient for possible surgery. The regression model linked the multiple patient variables to the outcomes of surgery, such as "no complications," "complications with morbidity," and "mortalities" over the different post-surgery time periods.

The decision-making needs for different roles are summarized in Table 1. At the clinical level, a typical scenario was applying information from past patient outcomes to better decide on the diagnosis and treatment of the current patient. At the facility level, outcome and utilization data on wait times, patient loads, prescription fill rates, and geographic dispersion of the patient helped form the basis for deciding suitable resources at a local or regional healthcare facility. At the policy level, comparing outcomes across facilities and regions, after adjusting for risks in the patient mix, enabled such decisions as identifying facilities for auditing and necessary improvement.
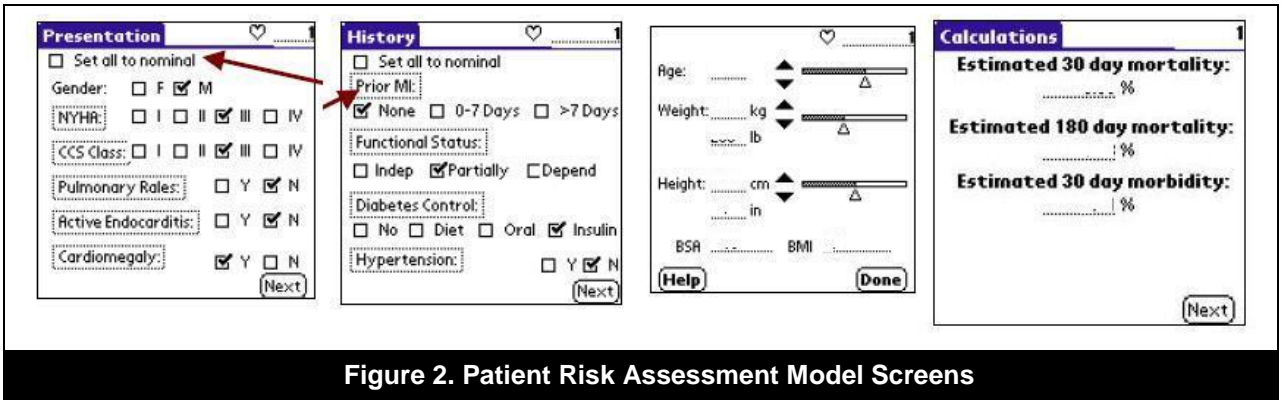
Figure 2. Patient Risk Assessment Model Screens

A SharePoint portal server distributed reports, summarizing and charting data in context-based views, that were dynamically created based on the accessing user's role in the healthcare system. By restricting views to only information that is relevant for each different level of user, such as at the patient care level, surgical program level, administration level, regional level, or national level, Health Insurance Portability and Accountability Act (HIPAA) rules are satisfied and users are not overloaded with irrelevant information. The reports had tabulated and charted data together with narratives on outcomes of surgeries by type of procedures, as well as surgical operative volume, outcomes of surgeries, risk estimates, complications rates, wait times, geographic distribution of patients, and adjusted and unadjusted outcomes of surgeries. The resource usage and process of care measures, such as length of stay and surgery time, were also tabulated and charted and presented in the report. Finally, the medication fill-rates data were also tabulated and charted and presented in the report.

Web servers published the at-a-glance performance dashboard, which facility administrators used to track outcomes and resource usage in order to decide on unit based resource allocation plans. The dashboards had multiple views selected using a navigation form (Figure 3) allowing comparison and a visual display of measures by category and over time.

The four dashboard views displayed data from the four categories of data: (1) review or outcome measures such as mortality and complications, (2) resource use measures such as wait time and ICU times, (3) process of care measures such as data on particular types of procedures, and (4) medication measures regarding rates of prescription fulfillment. There were three views of data in the dashboard: (1) category view, (2) center view, and the (3) single variable view. In the category view, the entire data set for one of the above data categories was presented for all centers over a single period of time. In the center view, the entire data set for one of the above categories was presented for a single center over a selected range of time periods. In the single variable view, a selected variable was displayed for a selected range of periods for all centers. Colors were used to help compare values among facilities. Patterns were also supported in the dashboard for black and white printing and non-color interpretation to accommodate users who wanted printouts and did not have a color copier.
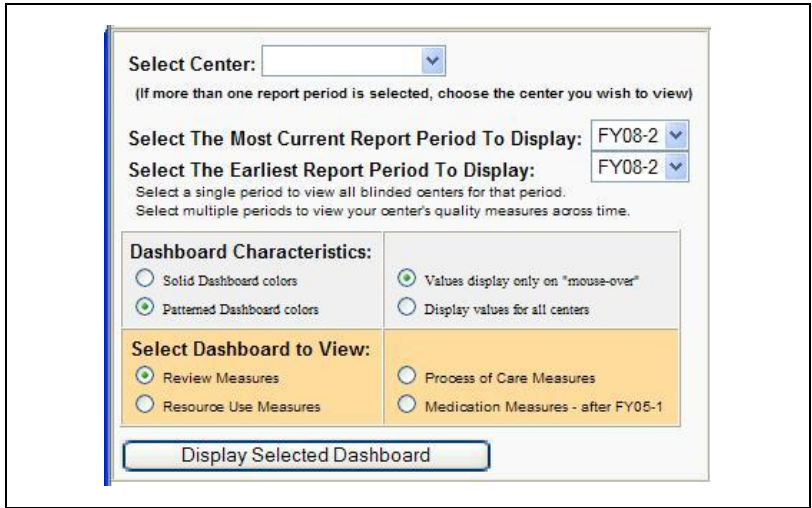
Figure 3. Dashboard Navigation Screen

Outputs Integrated to Organizational Processes

The outputs of the analytic capability were integrated to multiple operational and managerial processes. An Executive Board periodically reviewed cardiac surgery program performance across the VHA network. The outputs of the analytic capability allowed comparison of programs and their ongoing professional monitoring and evaluation of the quality and appropriateness of care and treatment of patients by the Cardiac Surgery Consultants Committee Board at the VHA. The board included reviews of risk adjusted and unadjusted operative mortality and morbidity at each VA medical center performing cardiac (open heart) surgery. The data supported the performance review processes of specialist medical staff such as surgeons, anesthesiologists, operating room nurses, intensive care nurses, and rehabilitation staff.

The output allowed the board to evaluate risk adjusted outcomes for quality assurance and compare facilities. Centers identified as performing below expectations conducted a medical chart audit and sometimes received a site visit [Hammermeister et al., 1994]. For example, any program that had a Coronary Artery Bypass Graft (CABG) or overall unadjusted cardiac surgical operative mortality greater than two times the VA national average for [each] period of six months, or greater than or equal to 10 percent, would have a paper audit of deaths occurring during that six-month period reviewed by the Cardiac Surgery Consultants Board. Any program that had greater than 5 percent based on Time Series Monitors of Outcome (TSMO) risk adjusted mortality criteria during the most recent three-year period, required a paper audit of all cardiac surgical mortalities occurring during the past six-month period based on a high mean Observed and/or Expected (O/E) ratio using a 90 percent confidence interval over time, unless the program had been audited or site visited within the last year.

Facility management processes, such as operating room (OR) staffing and scheduling process was done with the case load data reports. The volume of surgical cases handled by each facility and the geographic distribution of the patient load (drawn by zip code) was used to plan and continue the staffing of surgical programs. A number of subject matter experts, such as the surgical advisors, who served as network and facility liaisons used the data from the analytic capability to manage patient flow. They used the outputs to develop new programs and initiatives and to evaluate the utilization and allocation of selected treatments and procedures. Surgical services chiefs used the outputs in their monitoring processes and episode tracking. A list of additional processes that benefited from the outputs of the analytic capability are listed without details: (1) Quality assurance process to complement Surgical Complexity, (2) Assessment process for all surgical procedures, (3) Operating room utilization and efficiency, (4) Expanded specialty specific risk assessment process, (5) Surgical implant reporting process including wait times and outcomes and integration with the Veterans Implant Tracking and Alert System, and (6) the process of measuring Longitudinal functional outcomes of cardiac surgeries.

Measurement of Impacts

Criteria to gauge the analytic capability impacts are listed in Table 5. The patient care category benefits included reduction in errors, mortality, and morbidity [Grover, 2008; Grover et al., 2001; Hammermeister et al., 1994]. Improvement in patient safety, communications, and care standards were also measured. Care processes had reduction in wait time, length of stay, and duplication of record keeping. There were also improvements in workflow and compliance with medications.

Table 5: Patient and Care Process Measures		
Category	Benefit Measures	
	Reduction	Improvement
Patient Care	• Errors • Mortality • Morbidity	• Patient safety • Care standards • Care continuity • Patient communications • Outcomes–recovery rate
Care Processes	• Wait time • Length of stay • Duplication of record keeping	• Workflow • Compliance with medications • Treatment compliance rate • Standardization of treatment

VI. CONCLUSION

The Continuous Improvement in Cardiac Surgery Program (CICSP) successfully implemented an analytics capability using medical records from a wide variety of VHA facilities and practices. This capability was built on top of VHA's Vista Electronic Health Record (EHR) system and has been successful in driving decision-making by multiple roles.

The objective of this research was to identify from the VHA case study antecedents and key catalysts of an analytics capability. Specifically, we validated that the typical antecedents of an analytics capability, such as data collection, aggregation, data warehousing, modeling, and role-based output, also apply to healthcare. More importantly, we established the contribution of two catalysts to address the challenges specific to healthcare analytics capability. Our findings complement related research on heedful interactions for BI competency [Chasalow, 2009]. In the CoP heedful interacting occurs when many individuals work together as if they were of one mind [Chasalow, 2009; Dhillon, 2008; Weick and Roberts, 1993].

This VHA CICSP case study provides an example of an organization facilitating an analytic capability. It shows how a large-scale data driven analytic capability can be implemented to support multiple decision makers in a distributed organization. The VHA's analytic capability resulted in improved care processes and improved patient outcomes from these processes at a reduced cost. The success of such a program rested upon leadership to promote performance management and allocate resources for an appropriate architecture, skills, and technologies. At VHA, both automated tools and manual processes were essential for robust data collection and cleaning processes. The VHA CoP enabled data standardization by facilitating knowledge sharing. Ensuring accuracy in the input data enhanced trust and reliance on the outputs of the analytic capability. The resulting high quality analytic capability outputs improved care, accountability and reporting.

In summary, three lessons were learned on how leadership can facilitate an analytic capability:

1. *Emphasize Data Interoperability and System Quality*—Promote use of automated tools, manual EMR resolution and a CoP to (a) ensure the quality of the input data collection, (b) build trust in the reliability of system outputs, and (c) ensure semantic interoperability through data standardization for aggregation and comparison across the distributed organization. The VHA used a team of forty-five recording nurses—one per facility for each cardiac surgical program to support data quality and aggregation. Our data from the case study found that 80 percent of annual human resources deployed in supporting the analytic capability were in data aggregation, cleaning, and abstraction to support the ETL processes into the data warehouse.

2. *Support Effective Decision-making and Processes*—Allocate resources for an infrastructure that can tailor the system outputs to support users' tasks. Provide statistical risk models, reports, and dashboard views for users to access required information that supports effective decision-making at the appropriate level and for the relevant time period. The VHA case study findings supported the BI literature. We found that the benefits of BI result from the successful integration of analytic outputs into decision-making scenarios and processes. Also supporting stakeholders with data illustrated the benefits of using the analytic capability outputs [Shroyer et al., 2009].

3. *Measure Impacts*—Support measurement that evaluates system success, resource allocation, and accountability. Audit any centers performing below expectations. Measure continuing improvements in patient care and in care processes. Continuous feedback improves data and system quality that support more effective health assessment.

Limitations

As in any research study, this one has some limitations. With just one organization studied, we cannot ascertain the generalizability of our results. The VHA is not a typical organization because (1) it is not for profit, (2) it is a large and geographically dispersed entity and (3) its "customers" are not typical patients. Nevertheless, the achievements at the cardiac surgery unit of the VA can potentially be replicated in other units of the VHA and other health organizations.

Future Research

This research can be extended to a longitudinal study which follows the evolution of VHA's analytic capability. Research on other healthcare organizations can apply lessons developed here. Future research can determine whether these lessons have general applicability to other types of specialty care. Since cardiac surgery is considered the most complex of surgical specialty programs, the challenges are likely to be less for other surgical areas and other potential business processes. Future research can also determine whether the lessons are applicable in healthcare outside surgery as well as for many other organizations in a variety of industries. Many organizations can benefit from developing an analytic capability that enables establishment of risk models and dashboards based on high quality data. These models facilitate decision-making, improvement in processes, cost reduction and other measurable impacts.

The interpretation of the case study and recommendations presented in this paper are solely those of the authors. They do not in any way represent the views of the Department of VA or VHA.

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Editor's Note: The following reference list contains hyperlinks to World Wide Web pages. Readers who have the ability to access the Web directly from their word processor or are reading the article on the Web, can gain direct access to these linked references. Readers are warned, however, that:

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