2-14-2014

Ontology Driven Model for an Engineered Agile Healthcare System

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by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
Department of Electrical Engineering
College of Engineering
University of South Florida

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Date of Approval:
February 14, 2014

Keywords: Big Data, Systems Engineering, Control Systems, Modelling, System Design

DEDICATION

Dedicated to Dr. Moreno who has taught me “to do what I want to do and find passion in whatever I choose to do”. I am grateful for his tutelage, humbled by his deep and vast knowledge and simply lucky to have had a chance to work with someone truly inspiring and yet remarkably simple. While this dissertation is a closing chapter in over a decade long academic relationship, I look forward to continue learning from him how to be a man of conviction, passion and an engineer.

ACKNOWLEDGMENTS

I would like to acknowledge gratefully the committee that helped me through this journey. I sincerely appreciate their guidance and support. I would like to thank Tampa General Hospital for giving me the opportunity to develop, deploy and validate systems engineering processes and principles and for their executive support throughout this endeavor. I offer a very special note of thanks to Dr. Centeno for her counsel and advice. Her breadth and depth of knowledge is inspiring, as was her willingness to offer her repertoire while out on sabbatical. I want to acknowledge the staff at the Department of Electrical Engineering and the College of Engineering for their help and assistance. Finally, a special note of appreciation and thanks to Catherine Burton for her expertise and assistance in building this manuscript.

I believe that every human being possesses the quest to learn and that each of us is in search of a master. This master manifests itself in many forms. For some it is the form of a leader, for others a coach, a political leader or a religious figure. For me, the master comes in form of a teacher, Dr. Moreno, who gave me the priceless gift of learning and growing

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Healthcare is in urgent need of an effective way to manage the complexity it of its systems and to prepare quickly for immense changes in the economics of healthcare delivery and reimbursement. Centers for Medicare & Medicaid Services (CMS) releases policies affecting inpatient and long-term care hospitals policies that directly affect reimbursement and payment rates. One of these policy changes, a quality-reporting program called Hospital Inpatient Quality Reporting (IQR), will effect approximately 3,400 acute-care and 440 long-term care hospitals. IQR sets guidelines and measures that will contain financial incentives and penalties based on the quality of care provided.

CMS, the largest healthcare payer, is aggressively promoting high quality of care by linking payment incentives to outcomes. With CMS assessing each hospital's performance by comparing its Quality Achievements and Quality Improvement scores, there is a growing need and demand to understand these quality measures under the context of patient care, data management and system integration. This focus on patient-centered quality care is difficult for healthcare systems due to the lack of a systemic view of the patient and patient care. This research uniquely addresses the hospital's need to meet these challenges by presenting a healthcare specific framework and methodology for translating data on quality metrics into actionable processes and feedback to produce the desired quality outcome. The solution is based on a patient-care level process ontology, rather than the technology itself, and creates a bridge that applies systems engineering principles to permit observation and control of the system. This is a transformative framework conceived to meet the needs of the rapidly

changing healthcare landscape. Without this framework, healthcare is dealing with outcomes that are six to seven months old, meaning patients may not have been cared for effectively.

In this research a framework and methodology called the Healthcare Ontology Based Systems Engineering Model (HOB-SEM) is developed to allow for observability and controllability of compartmental healthcare systems. HOB-SEM applies systems and controls engineering principles to healthcare using ontology as the method and the data lifecycle as the framework. The ontology view of patient-level system interaction and the framework to deliver data management and quality lifecycles enables the development of an agile systemic healthcare view for observability and controllability.

CHAPTER 1: INTRODUCTION

The current state of the U.S. healthcare delivery system is well documented and analyzed [1-8]. This analysis has exposed the disconnect between healthcare costs and clinical quality outcomes. Healthcare cost is now a major proportion of the economy while a majority of the population still battle chronic conditions that require care management and about a half of those have multiple conditions. As a society, we have admired and debated this problem for decades. This debate has resulted in massive technology investments, increasing governmental influence and arguably, influenced the outcomes of a few elections. Nevertheless, the issue still looms large. While healthcare is often a "life or death" contemplation, fraught with emotion, it is important that we do not generalize it as just another sector of the economy. According to Centers for Medicare & Medicaid Services (CMS) - National Health Expenditure Projections 2011-2021, healthcare spending in 2014 will grow by 7.4% [9]. CMS also anticipates that healthcare spending growth will average 6.2% annually between 2015 and 2021.

While healthcare spending is projected to reach 19.5% of the GDP by 2017 [10], the gap between cost and quality has widened. CMS recently updated care performance expectations that will guide the payment criteria, the payment rates and other policies for inpatient care and long-term care hospitals. One of the new health care expectations is an initiative designed specifically to impact quality and improve outcomes called the Hospital Value Based Purchasing (VBP) program. The goal of this program is to transform the largest payer, Medicare, to a purchaser of service value, moving away from a purchaser of service delivered. In short, CMS will pay for quality of care – based on patient outcomes, rather than an institutional cost to provide the care - impacting approximately 3,400 acute-care hospitals and approximately 440 long term care hospitals.

As a Nation, we grapple with an aging population making it imperative that we develop care delivery systems that will withstand the load and scale without jeopardizing future generations. Some of the current healthcare system's problems have an engineering solution and this research focuses on developing an engineering solution to help address them.

For the first time, CMS is imposing both penalties and incentives based on performance. With increasing pressure to lower healthcare costs, this path is gaining traction. Given that Medicare and Medicaid are the largest payers in the country, it is expected many private insurers will follow suit. This penalty/incentive approach will place immense pressure on hospitals and force other covered entities to reinvent themselves to meet these challenges. This is amplified by the fact that there is a growing pressure to lower reimbursement costs and the outcome of the Affordable Care Act (ACA).

The pressure on hospital systems to improve quality outcomes and to lower costs has resulted in a massive rush to invest in technology. This rush to investment over the last 7 years can be clearly measured by the maturity and adoption model, called Electronic Medical Record Adoption Model - EMRAM^{SM}, developed by Healthcare Information Management Systems Society (HIMSS) [11]. Table 1 shows the different adoption stages ranging from 0 to 7 and their respective capabilities. By the second quarter of 2013, the data show a skewed adoption curve peaking around Stage 3, highlighting the lack of maturity in healthcare technology adoption.

This rapid investment in technology was precipitated by the incentives offered by the Health & Human Services. Figure 1 and figure 2 show how hospitals and physicians are achieving standards for health IT incentives [12].

Healthcare's massive investments in technology, ostensibly to replace outdated manual processes, were rapid and concentrated to the last ten years. While in many cases the technology resulted in streamlined and better-coordinated care, it too often resulted in the deleterious effect of 'systemizing' bad paper practices. With increasing pressure to meet new initiatives such as VBP, it became imperative to use not only the technology platform but to evaluate care in a more systematic and holistic way.

This dynamic transformation in evident with the increasing number of quality measures that are coming out of regulation and being adopted by the payers. To adequately meet the needs of this explosion in quality measures, effective and efficient data analytics and a systemic view of care is critical.

Despite massive technology investments, gaps remain - glaring are the manual and error prone chart abstraction processes necessary to gather and verify the metrics required by CMS. This is not just an abstraction issue, but also an interpretation issue. Care delivery is a complex science and the processes for care, quality and data interpretation are not consistent. Currently, measures such as VBP require the abstractor to review each patient record, manually locate proper documentation to respond to each metric. Paper forms are filled out by with patient demographics, patient diagnoses and procedure codes, and drug administration details. After the chart abstraction is complete, a subset of records is selected for a pre-submission clinical review as part of an internal audit process. Once the clinical review is complete, the abstraction results are entered manually into an error checking process (usually a third party software application) and only then submitted to CMS. If errors are detected the record is sent back to the abstraction team for further review. Additionally, any error found in diagnoses or procedure codes is returned to coding for correction. These modifications can add considerable delay in processing the data. Figure 3 shows the process flow described above.

The need to automate the data extraction process particularly as it pertains to quality of care reporting is mounting. The goal is to shift the paradigm - from the tedious task of manually searching through records to locate relevant information to pertinent data automatically identified by technology, significantly saving time and reducing errors. Through automation and increased data capture, the validation and verification of this data can be performed on structured data, such as International Statistical Classification of Diseases and Related Health Problems (ICD) codes and patient demographics. Hospitals can then reassign these resources for concurrent monitoring and improve quality while the patient is still under their care.

Manual processes are a significant healthcare problem with a specific systems engineering solution. Through this dissertation, we establish a framework for applying systems engineering principles to healthcare for the betterment of the patient and the improvement in the quality of care and ultimately the patient outcome.

Table 1: United States EMR Adoption Model SM [11]

Stage	**Cumulative Capabilities**	**2013 Q1**	**2013 Q2**
Stage 7	Complete EMR; CCD transactions to share data; Data warehousing; Data continuity with ED, ambulatory, OP	1.9%	2.1%
Stage 6	Physician documentation (structured templates), full CDSS (variance & compliance), full R-PACS	9.1%	10.0%
Stage 5	Closed loop medication administration	16.3%	18.7%
Stage 4	CPOE, Clinical Decision Support (clinical protocols)	14.4%	14.6%
Stage 3	Nursing/clinical documentation (flow sheets), CDSS (error checking), PACS available outside Radiology	36.3%	34.5%
Stage 2	CDR, Controlled Medical Vocabulary, CDS, may have Document Imaging; HIE capable	10.1%	9.0%
Stage 1	Ancillaries - Lab, Rad, Pharmacy - All Installed	4.2%	3.8%
Stage 0	All Three Ancillaries Not Installed	7.8%	7.2%
Data from HIMSS Analytics® Database ©2012		N = 5441	N = 5439

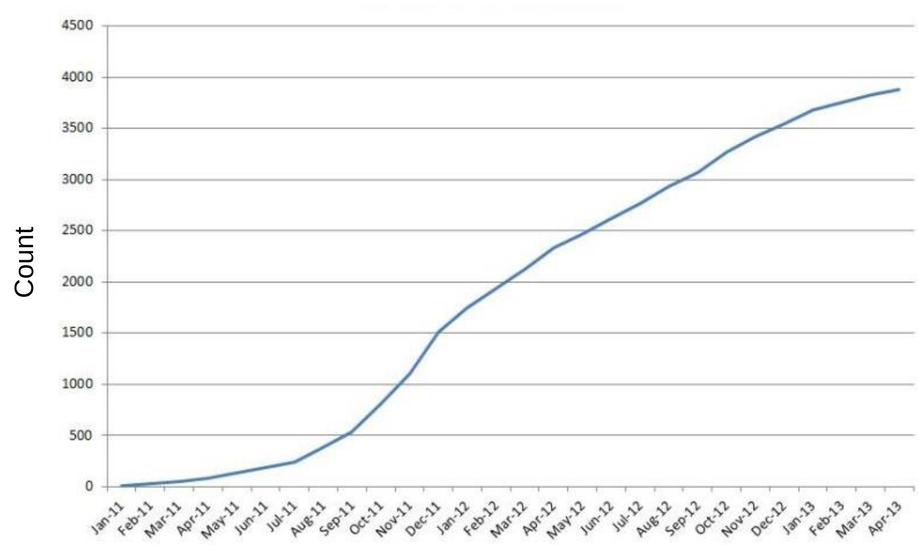

Figure 1: Eligible hospitals achieving standards for health IT incentives

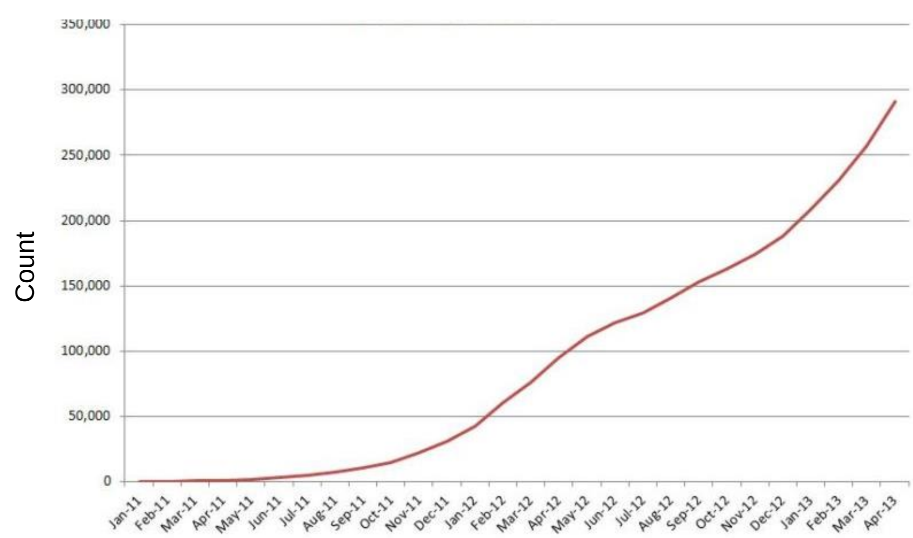

Figure 2: Physicians and other providers achieving standards for health IT incentives

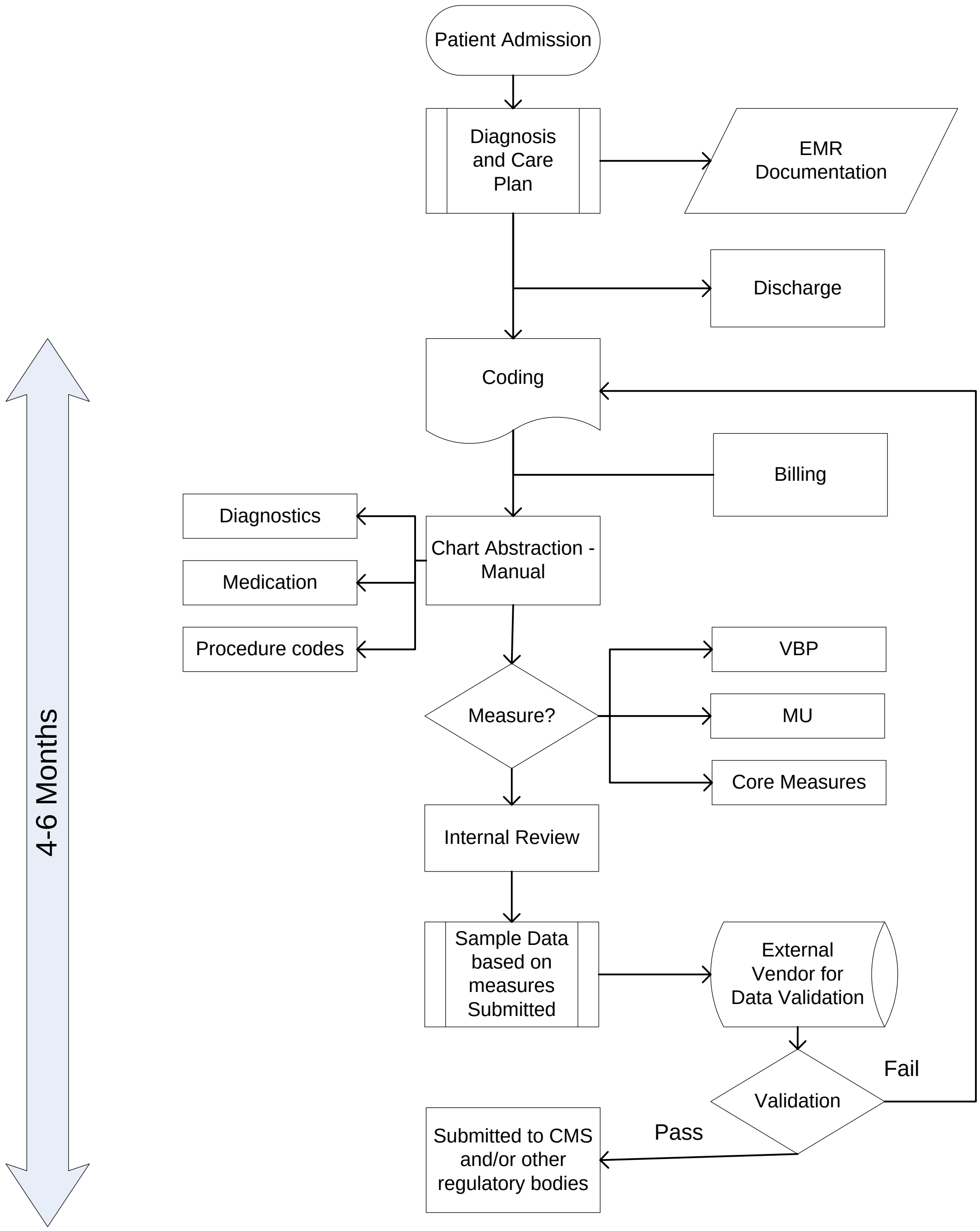

Figure 3: Manual data abstraction and reporting process

CHAPTER 2: LITERATURE REVIEW AND RESEARCH OBJECTIVE

2.1 Status of Current Literature

To understand and better dissect the cross section of healthcare relevant to this research it is critical to start with the following breakdown. The criticality is based on need to understanding and connect the patient care and quality outcomes to better data management and governance and how everything works together from a system integration perspective.

1. Patient Care Quality Outcomes - Patient Care and Quality Outcomes is the sole responsibility of the care provider and hospitals.
    a. Quality and Policy (Q) – Driver for patient care and quality outcomes influenced by policies for specific quality outcomes.
    b. Economics (E) – Motivation for achieving quality outcomes that are either legislated and/or industry driven is incentivized in payment structure.
    c. Modelling (M) – Understanding of how data is derived endorsed and measured.
2. Data Management – Understanding the need for managing data that can be translated into intelligence.
    a. Standardization (S) – Driver for achieving a structured view of data to allow for better process control.
    b. Analytics (A) – Ability to apply data to actionable information.
3. Systems Integration – Ability to understand how technologies and process are intertwined to allow for an ontological view of patient, care and outcomes continuum.
    a. Workflow Process (W) – Understanding the relevance of workflow process mapping to under the underlying quality or any other desired outcome.

b. Technology Integration (T) – Integrated view of how technology is applied from an enterprise stand point.

In the following sections, the topics are expanded with relevant literature associated with each of these components.

2.2 Patient Care Quality Outcomes

The incentive payment model under the Affordable Care Act has put a lot of focus on the clinical process of care, outcomes and performance scores to the point where reimbursement is no longer based on the quantity of services provided. [13].

Policy coming out of current legislation is matching incentive-based payment models to quality of the patient care outcomes. These policies are modelled using measures that changes outcomes at the hospital-level and associated with risk standardized payment for key performance measures [13]. These modelled quality and policy outcomes have a profound impact on reimbursements, leading to wide economic impact. Care providers and the healthcare systems are gearing up for this impact, which is aimed at cost containment and quality improvement.

2.2.1 Quality and Policy

Hospital Value Based Purchasing (VBP) is a program designed to improve clinical processes, outcomes and performance scores through monetary incentives and penalties [14]. This program proposes and encourages a reporting infrastructure for hospital Inpatient Quality Reporting (IQR) measurement. To make business process changes and achieve performance scores, a business process analysis and methodology that integrates quality metrics to healthcare environment process needs to be identified and studied [15]. This push for driving quality through policy is already reflected in two measures that are being reported: mortality rates and readmission rates.

Hospital performance is classified by CMS into three quality measure sets [16]. The literature is clear: direction of all healthcare policies point toward increasing incentives forhigher performing organizations and withholding reimbursement for lower-performing organizations based on the quality measure outcomes. The policy clearly regulates that the total amount of value-based incentive payment to maintain budget neutrality. The policy also dictates that the re-distribution of federal reimbursement should be allocated among all participating hospitals based on performance scores [14]. Similar programs such as Meaningful Use are also pushing policy in this direction. [17].

2.2.2 Modelling

It is critical to understand the quality and policy measure from its inception to development and implementation. The approach for measure development is central to understanding the outcome expected. National Quality Forum (NQF) develops measures applied universally to improve outcomes. Understanding how the measurements are selected, measured, endorsed for adoption and most importantly, how they are mathematically derived, is critical to developing processes that will help change the outcome. NQF uses very strict guidelines before endorsing any of the measures that are adopted. This section reviews how the measures are mathematically derived and scientifically vetted for usability and feasibility. Hierarchical generalized linear models are applied to the analysis of healthcare utilization data [18]. This modelling methodology is applied to define readmission measures using hierarchical logical regression and develop a Risk-Standardized Readmission Rate (RSRR) for hospitals to reflect quality [19].

2.2.3 Economic Impact

The National Hospital Discharge Survey (NHDS) has been collecting data since 1965 and among others collect information about the inpatients discharged from hospitals in the United States. These data are used to extrapolate that Medicare currently pays for 40-50% of hospitalizations nationally [8], making CMS the biggest payer in the country. Any changes in reimbursement based on quality metrics will have far-reaching impact to the healthcare economy. Meaningful Use incentives have enabled the comparison of Healthcare Effectiveness Data Information Set (HEDIS) medications based on very specific specifications [17]. The literature is clear in stating the benefits of provider performance transparency, including discovery of medical errors, empowerment of patients and focused regulation in a pay-for-performance environment [20].

2.3 Data Management

Data are the essential components of any process, and healthcare, as a complex and process driven system, is heavily reliant on data [21]. Data management has an important role in process control and is fundamental to how patient quality outcomes are developed and quantified. It is clear that data are the central pieces in developing quality metrics. It is equally important to look at the application of data by the providers and hospitals that affect outcomes. This focus on data is conducted under the standardization and analytics category. Without standardization, analytics is incomplete and without analytics the desired outcome cannot be measured.

2.3.1 Standardization

The overview of quality standardization is uncomplicated. The reimbursements from Medicare, taking into account payment adjustments for geography and policies, dictate the hospital practice patterns [13]. The data around broad categories such as mortality and readmissions are clearly standardized allowing the development of measures such as "death from any cause within 30 days of a hospitalization" and "readmission for any reason within 30 days of discharge" [16]. The advancements in standardization have allowed us to predict the relation between the different domains of care [22]. The diversity of data at the provider level is fuelling the need for hospital level standardization contributing to the growing focus on data warehousing [23].

2.3.2 Analytics

Infusion of healthcare technology has caused an explosion in health care data. However, this data must be analyzed in order to become useful information. The process of converting raw data into intelligence is called analytics and health care as an industry is exploding with data that needs to be managed as a clinical and financial asset. The adoption of national metrics is exposing the gaps in standardization [24]. The heretofore absence of managing data as an asset is creating a need that for comprehensive analytics programs can fulfill. Big data is forcing healthcare institutions to develop methodologies that manage acquisitions of new data, data standardization, schema development and data integration and optimization [25]. However, the literature points to the lack of a holistic strategy to deal with the big data in healthcare [26].

Analytics is the biggest opportunity in healthcare today and is currently underutilized due to the limitations presented by the lack of ontological view of healthcare [27]. The result - a disconnect between data and decision support systems [28].

2.4 System Integration

Healthcare is a complex system composed of adaptive people and processes. It is an amalgamation of biomedical, chemical, electrical, environmental, industrial, material and mechanical systems [21]. One of the most pressing challenges is the need to integrate effectively these systems for the improvement in the patient's care. However, the study of system integration is incomplete without understanding how a workflow or process will affect data and quality outcomes. Technology drives process, and we expect that the integration of workflow and process to technology will help guide outcomes.

2.4.1 Workflow/Process

At a fundamental level, system redesign with system engineering tools has been proven to improve patient safety [29]. The process-level integration of complex systems is studied from the need for workflow integration between the aspects of this complex system [30]. The need for workflow and process standardization has an impact on patients and care provider's perspective of usability and usefulness of data and information having significant impact on quality and outcomes performance [31].

2.4.2 Technology Integration

Technology integration in healthcare is studied from the need for developing billing and payment mechanisms, clinical integration and data collection [32]. Technology integration is considered to bring platform interaction for patient safety and technology management for clinical engineering [33]. Requirements for cross platform integration and study has propelled the need for data integration to serve healthcare regulators, physicians, hospital administration and consumers [23].

The multidisciplinary nature of healthcare has resulted in fractured technology platforms making holistic, patient-centric analysis unnecessarily difficult. The literature confirms a lacks of a global (holistic) view of patient level ontology knowledge framework.

Given the breadth of the areas addressed in this research, a large body of literature was reviewed and organized under the categories listed in Table 2. Healthcare literature also confirms the data decentralization aspect of this industry. Knowledge and process are distributed between provider and clinical research, policy, data management, clinical practices, technology and system integration. The performance of imperfect modelling in healthcare has been studied at the most basic level to understand the strengths and weaknesses of data and quality models [34]. This suggests that healthcare is still a maturing industry when it comes to data modelling. Regardless, this imperfect modelling is used to set major outcome and quality metrics both from policy and legislatives perspectives. There is extensive work in business process analysis for process mining [35], but these process analysis and mining are more of an adoption for healthcare and not developed specifically for healthcare. To create the process map and the analysis that will impact outcomes requires a strong infrastructure and a digital framework [30]. While the need is clear, the infrastructure for a clinical-engineering framework has not been designed. And while the impact of standards in quality reporting is well studied, the literature suggests closing the gaps in electronic quality measures, process and standards [24]. The lack of standardization presents ethical issues [36] and the need for a systemic view of healthcare is critical to solve this issue.

2.5 Research Objective and Strategy

Through a detailed review of the literature, the following gaps have been identified:

1. The modelling, leading to legislated metrics, does not match a consistent process
2. Lack of process integration in hospitals leads to a lack of outcomes mapping to a process [15]
3. No systems level programmatic view to link process to desired outcome
4. Programs are designed around “mandated” quality and not around quality outcomes
5. Looming “Regulatory” requirements further demand the need to integrate data into process
6. Fragmented data sources lead to inaccurate data analysis and lack of a global view [37]

In summary, there is a lack of a unified patient-centric framework allowing data, technology, clinical and feedback process to be integrated systematically that can impact outcomes and quality of care. This is having a profound impact on the quality metrics.

Based on these opportunities within the literature, and the current business structures – which calls for immediate attention and action, this research focuses on the following:

1. Methodology: Create a patient-centered ontology in a hospital setting to map system level eco-system for a Healthcare Data Architecture
2. Framework: Design a system that utilizes data and process ontology to data governance model and allow for feedback and overall quality and outcomes management

Figure 4 represents the systemic view of the model that incorporates the methodology and framework to create outcomes that are controlled and observed within a finite time. Data is collected in various sources and is the input for this system. Using health care ontology, these sources are mapped to produce the desired quality outcome. This is governed by the data life cycle framework. The methodology, framework and the outcome is the system. The final output of this system is the quality of care. Given that this is patient care, the finite time as defined in controls and systems engineering, is defined as the patient encounter. This structure is the Healthcare Ontology Based Systems Engineering Model (HOB-SEM) allows for observability and controllability of the healthcare system, defined as the quality of care provided during the patient encounter.

This research uses ontology to develop a systemic view towards measuring, controlling and observing healthcare data. Since the focus is on the quality of care, this Healthcare Ontology Based Systems Engineering Model (HOB-SEM) is designed to monitor and control quality metrics. HOB-SEM can be applied to all aspects of healthcare, whether surgical services or the emergency department, due to the systems engineering foundation.

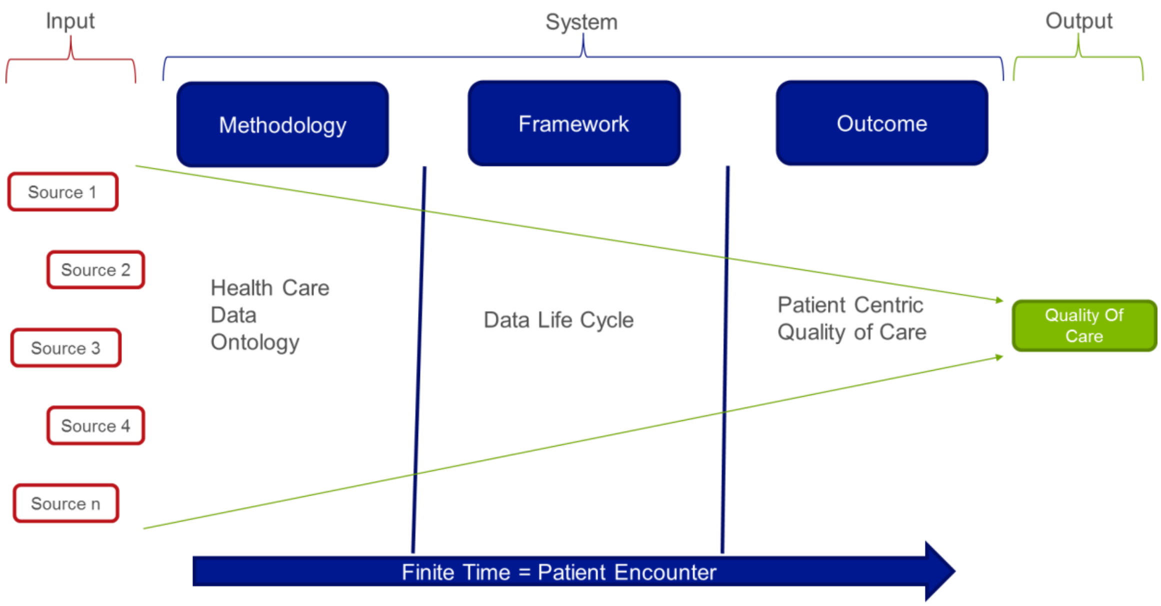

Figure 4: Systemic view of HOB-SEM

While significant amount of research has been done in data modelling, quality metrics and technology, this research advances systems engineering in healthcare administration and management by directly affecting quality of care and outcomes. Healthcare has been reactive to the social and political changes and this research develops a novel framework that will enhance the infrastructure for patient quality of care, giving systems engineering an active role in hospital management. In addition, through this work a unique and creative partnership with patients, caregivers (physicians, nurses and others), data scientists and engineers is created to develop a systemic framework for data management. Moreover, it outlines the shift in how frameworks should be developed to match the desired business outcomes, contributing to a platform of thinking that could be applied to industries looking for operational or strategic effectiveness and efficiency.

Table 2: Contribution of the published work to the categories under study

Q=Quality and Policy E=Economics M=Model S=Standardization A=Analytics
W=Workflow/Process T=Technology Integration

Year	**Ref #**	**Title**	**Main Contribution**	**Patient Care Quality Outcomes**			**Data Management**		**System Integration**		**Relevant Considerations**
				Q	**E**	**M**	**S**	**A**	**W**	**T**	
1994	[31]	Measuring the Quality of Healthcare	Tests the validity of (theoretical) quality framework within an empirical analysis.			**X**	**X**				Analysis confirms the predicted causality between the different dimensions of quality of care for the German federal states
1996	[32]	Integrated health systems. Information Knowledge Systems Management	Identifies the fragmented nature in which healthcare is financed and delivered					**X**		**X**	Impact of system engineering methods is enhanced through the integration of processes, goals and outcomes.
1998	[15]	How Well Do Models Work? Predicting Healthcare Costs. Proceedings of the Section on Statistics in Epidemiology	Explores alternative measures and methods for describing and comparing models that predict expected costs of people who sign up for health plans (such as HMOs).			**X**					Develops a range of numerical summaries and graphical displays which can be used to create rich pictures of model performance. These ideas are useful at the most basic level of understanding the strengths and weaknesses of any imperfect model.
1999	[17]	Hierarchical Generalized Linear Models in the Analysis of Variations in Healthcare Utilization	Design a broad class of hierarchical generalized linear models (HGLMs) and discuss their applications to the analysis of healthcare utilization data			**X**					The model incorporate covariates at each level of the hierarchical data structure, can account for greater variation than what is allowed by the variance in a one-parameter exponential family, and permit the use of heavy-tailed distributions for the random effects

Table 2 Continued

Year	Ref #	Title	Main Contribution	Patient Care Quality Outcomes			Data Manageme nt		System Integration		Relevant Considerations
				Q	**E**	**M**	**S**	**A**	**W**	**T**	
2001	[23]	Healthcare data warehousing and quality assurance	Lists the rife with often-incompatible medical standards and coding schemes that require careful translation.				**X**			**X**	Healthcare data warehousing will make rigorous, quantitative information available to healthcare decision makers. Results derived from a healthcare data warehouse must be delivered in accessible form to diverse stakeholders, including healthcare regulators, physicians, hospital administrators, consumers, community activists, and members of the popular press.
2003	[28]	Analysis of healthcare quality indicator using data mining and decision support system	Presents an analysis of healthcare quality indicators using data mining for developing quality improvement strategies			**X**	**X**				Decision support system (DSS) is developed to analyze and monitor trends of quality indicators using Visual Basic 6.0. Guidelines and tutorial for quality improvement activities were also included in the system
2007	[37]	Statistical and C linical Aspects of Hospital Outc omes Profiling	Report card based evaluation			**X**					Historical evolution of hospital profiling with special emphasis on outcomes; present a de- tailed history of cardiac surgery report cards, the paradigm for modern provider profiling
2008	[34]	An ontological knowledge framework for adaptive medical workflow	Develops a model with the vision of personalized healthcare possible by capturing all necessary knowledge for a complex personalized healthcare scenario involving patient care, insurance policies, and drug prescriptions, and compliances.							**X**	Presents an ontological knowledge framework that covers healthcare domains that a hospital encompasses—from the medical or administrative tasks, to hospital assets, medical insurances, patient records, drugs, and regulations.

Table 2 Continued

Year	Ref #	Title	Main Contribution	Patient Care Quality Outcomes			Data Management		System Integration		Relevant Considerations
				Q	E	M	S	A	W	T	
2009	[25]	Methodologies for Data Quality Assessment and Improvement	Due to the diversity and complexity of these techniques, research has recently focused on defining methodologies that help the selection, customization, and application of data quality assessment and improvement techniques.					X			Methodologies are compared along several dimensions, including the methodological phases and steps, the strategies and techniques, the data quality dimensions, the types of data, and, finally, the types of information systems addressed by each methodology.
2009	[29]	Patient safety: The role of human factors and systems engineering	Identifies the need for increasing partnerships between the health sciences and human factors and systems engineering to improve patient safety.				X				Lays out the approaches to patient safety and system redesign with systems engineering tools that can be used to improve patient safety.
2009	[21]	Healthcare: A complex service system	Discusses techno biology approach of systems engineering to underpin its development as an integrated and adaptive system				X			X	Healthcare can be considered to be of three essential components – people, processes and products.
2010	[36]	A Lack of Standardization: The Basis for the Ethical Issues Surrounding Quality and Performance Reports	Advocates a standardized ethical framework to guide current and future development and implementation of performance reports			X	X				Develops framework which would resolve a number of the major issues, includes the following ethical principles to guide the practice of public reporting on the Internet and facilitate enhanced quality improvement in the healthcare

Table 2 Continued

Year	Ref #	Title	Main Contribution	Patient Care Quality Outcomes			Data Management		System Integration		Relevant Considerations
				Q	E	M	S	A	W	T	
2011	[33]	Health technology management: A database analysis as support of technology managers in hospitals	An easy and sustainable methodology is vital to Clinical Engineering (CE) services in healthcare organizations in order to define criteria regarding technology acquisition and replacement.						X	X	This article underlines the critical aspects of technology management in hospitals by providing appropriate indicators for benchmarking CE services exclusively referring to the maintenance database from the CE department
2011	[30]	Highlights From the Third Annual Mayo Clinic Conference on Systems Engineering and Operations Research in Healthcare	Focuses on the systems engineering aspect of coordinating, synchronizing and integration of complex systems of personnel, information, materials, process, facilities and financial resources.						X		Proposes the need for a robust digital infrastructure for a clinical-engineering partnership.
2011	[38]	Quality Measurement of Medication Monitoring in the "Meaningful Use" Era	Compares the measured quality of laboratory monitoring of Healthcare Effectiveness Data and Information Set (HEDIS) medications based on specifications.	X	X					X	Measured the prevalence of ordering and completion of laboratory tests monitoring HEDIS medications
2012	[19]	2012 Measures Maintenance Technical Report: Acute Myocardial Infarction, Heart Failure, and Pneumonia 30-Day Risk Standardized Readmission Measure	Defines admission measures use hierarchical logistic regression modeling to create a RSRR at the hospital level that reflects hospital quality.			X					The measures incorporate administrative claims data for each patient from one year prior to and including the date of the index hospital admission to adjust for case-mix differences at hospitals.

Table 2 Continued

Year	Ref #	Title	Main Contribution	Patient Care Quality Outcomes			Data Management		System Integration		Relevant Considerations
				Q	E	M	S	A	W	T	
2012	[35]	Business process analysis in healthcare environments: A methodology based on process mining	Performing business process analysis in healthcare organizations is particularly difficult due to the highly dynamic, complex, ad hoc, and multi-disciplinary nature of healthcare processes	X			X				Methodology in a tool that integrates the main stages of process analysis. The tool is specific to the case study, but the same methodology can be used in other healthcare environments.
2012	[31]	Healthcare management through organizational simulation	Developed Health Advisor, a web-based game using organizational simulation to empirically study alternative means of delivery that do not yet exist.						X		Quantifies people's perceptions of the usability and usefulness of information sources have a strong impact on the use of these sources, and a significant impact on their subsequent performance in diagnoses and referrals
2012	[24]	The impact of emerging standards adoption on automated quality reporting	Analyzes the effectiveness of Automated quality reporting, considered by many to be an important tool that will help close the gaps in the quality of US health by increasing the timeliness, effectiveness, and use of quality assessment					X			Identifies the greater need for around initiatives that address the gaps in electronic quality measurement standards and processes, including strong Federal involvement and guidance
2012	[27]	Towards an ontology for data quality in integrated chronic disease management: A realist review of the literature.	Effective use of routine data to support integrated chronic disease management (CDM) and population health. An ontological approach to DQ is a potential solution but research in this area is limited and fragmented.					X	X		Identify mechanisms, including ontologies, to manage DQ in integrated CDM and whether improved DQ will better measure health outcomes.

Table 2 Continued

Year	Ref #	Title	Main Contribution	Patient Care Quality Outcomes			Data Management		System Integration		Relevant Considerations
				Q	E	M	S	A	W	T	
2012	[14]	Hospital Value-Based Purchasing – Frequently Asked Questions	Funding and quality based incentive program is defined and quantized.		X		X				This documents sets final achievement thresholds and benchmarks along with clinical process of care domain scores.
2013	[13]	National Provider Call: Hospital Value-Based Purchasing	To propose Value Based Purchasing, Clinical Process of Care, Outcomes, Total Performance Score and Incentive.	X	X						Categorization of quality incentive program for hospital inpatient quality reporting (IQR) measure reporting infrastructure
2013	[26]	Healthcare's "Big Data" Challenge.	Presents comments on managing big data to address persistent cost and quality deficiencies in the healthcare system				X				Conceptually discusses the need for continual technical advancement needed to store and efficiently access the big data like symptoms, physical signs, orders and progress notes are entered generally through human being.
2013	[20]	Performance Data Collection as a Means to Measure Providers' Quality of Care	Identifies benefits of provider performance transparency, including discovery of medical errors, empowerment of individuals as consumers, promotion of providers' internal learning, ability of government to focus regulation, and payers' use in pay-for-performance.		X						Governments, providers, payers, and private accreditors all seek and potentially benefit from the collection and analysis of performance data. Transparency of performance allows individual consumers to make informed decisions.
2013	[39]	Medical Ontology in the Dynamic Healthcare Environment	Applies ontology to healthcare IT systems.							X	Applies the concept of service oriented architecture (SOA) to manage the healthcare complexity with the help of ontology.

Table 2 Continued

Year	Ref #	Title	Main Contribution	Patient Care Quality Outcomes			Data Management		System Integration		Relevant Considerations
				Q	E	M	S	A	W	T	
2013	[40]	A three stage ontology-driven solution to provide personalized care to chronic patients at home	Application of ontology to patient monitoring for different morbidities.							X	Applies ontology to home based tele-monitoring for certain chronic conditions. Develops a three step ontology based approach for this unique issue.
2013	[41]	A four stage approach for ontology-based health information system design	Application of ontology to developing a Health information system, using a hybrid participatory design – grounded theory.							X	Applies ontology to the design and implementation of a health information system using a four step process.
Current	[18]	Performance Report on Outcome Measures	Hospital Quality Chart book explores hospital performance on three quality measure sets: the publicly-reported mortality and readmission measures for acute myocardial infarction (AMI), heart failure, and pneumonia;	X		X	X				The mortality measures assess death from any cause within 30 days of a hospitalization (regardless of whether the patient dies while still in the hospital or after discharge).
Current	[16]	National Hospital Discharge Survey.	Survey designed to meet the need for information on characteristics of inpatients discharged from non-Federal short-stay hospitals in the United States		X						Integrates inpatient data formerly collected by the NHDS with the emergency department (ED), outpatient department (OPD), and ambulatory surgery center (ASC) data

CHAPTER 3: HEALTHCARE ONTOLOGY

Over the last 15 years, the healthcare industry has tried to collaborate with industries in the fields of logistics, transportation, communication and retail in incorporating and utilizing technology. In contrast, most corporations in these environments have matured in technology applications and embraced automation and rapidly evolved towards enterprise architecture, healthcare has evolved slowly and finds itself in what is has come to be called the "best of breed" strategy. While the best of breed strategy served the purpose of keeping up with the multitude of and unique service lines within a hospital, it resulted in technology silos (management systems that are unable to operate with any other systems). However, over the last 10 years, hospitals have heavily invested in "Electronic Medical Record" (EMR) in an attempt to create an enterprise view of patient related information. This expansion in technology has created a flood of computer applications built for different services and did not necessarily have an enterprise view, resulting in the creation of multiple platforms, data architectures and programming languages effectively restricting data flow and integration [39]. Despite the progress made through EMR investment, silos remain due to the lack of ontologies that define the hierarchical components and descriptions of the properties of all the important domains within healthcare.

The logical step to dissolving these silos is to create a unified view of the industry. Enterprise Architecture (EA) provides a holistic system-level view by systems thinking, principles, and disciplines of engineering and architecture [42]. Without the holistic EA view, outcomes are disconnected in terms of activities, tools, groupings, models and even nomenclature. As identified in research literature [39], one of the key aspects of an enterprise-level view is the ability to describe an ontology for every piece of information.

"*Ontology is the philosophical discipline which aims to understand how things in the world are divided into categories and how these categories are related together. This is exactly what information scientists aim for in creating structured, automated representations, called 'ontologies,' for managing information in fields such as science, government, industry, and healthcare. Currently, these systems are designed in a variety of different ways, so they cannot share data with one another. They are often idiosyncratically structured, accessible only to those who created them, and unable to serve as inputs for automated reasoning*."[43]

According to a recent paper by Zeshan [39], there are three major uses for an ontology:

1. to assist in communication between humans,
2. to achieve interoperability,
3. to facilitate communication among software systems.

While these uses can be applied to any industry under study, healthcare can acutely benefit from the application of ontology since h andoff communication, data across specialties and integration are critical to patient care.

With the goal of access to real-time, quality of care data, the methodology will map out the patient, the caregiver and the technology level ontology. Based on that, a healthcare specific data architecture with ontology will be built. This methodology will be applied in the development and application of a framework that will allow for coherent data governance and the application of knowledge - through data to information - to manage healthcare as a system.

3.1 Patient Flow

Derivation of intelligence from the effective integration of data/information from heterogeneous sources; to identify domains, relationships, entities, events and categories to study the nature of being or quantifiably observe or control the system is the definition of ontology applied in this research. To start from the highest level of defining the ontology, patient flow is studied and mapped. The Emergency Department (ED) is one example of study along with surgical services, pharmacy and bed management. Modeling approaches varying from a closed, re-entrant process model leading to patient's length of stay calculation to patient satisfaction based on ED flow [44] have been studied and developed. Similar studies can be found in other areas of the healthcare continuum. Figure 5 identifies a patient flow process through the continuum. In this example, a patient arriving in ED is walked through the registration process, leading to triaging and a possible diagnosis and monitoring. While this happens, depending on the condition of the patient, a detailed registration is completed. In this scenario, while preliminary tests are ordered, a surgical consultation results in routing the patient through surgical services and eventually transferring to an inpatient setting. While the patient is discharged with proper medication, the chart is coded for billing which is submitted to the payer.

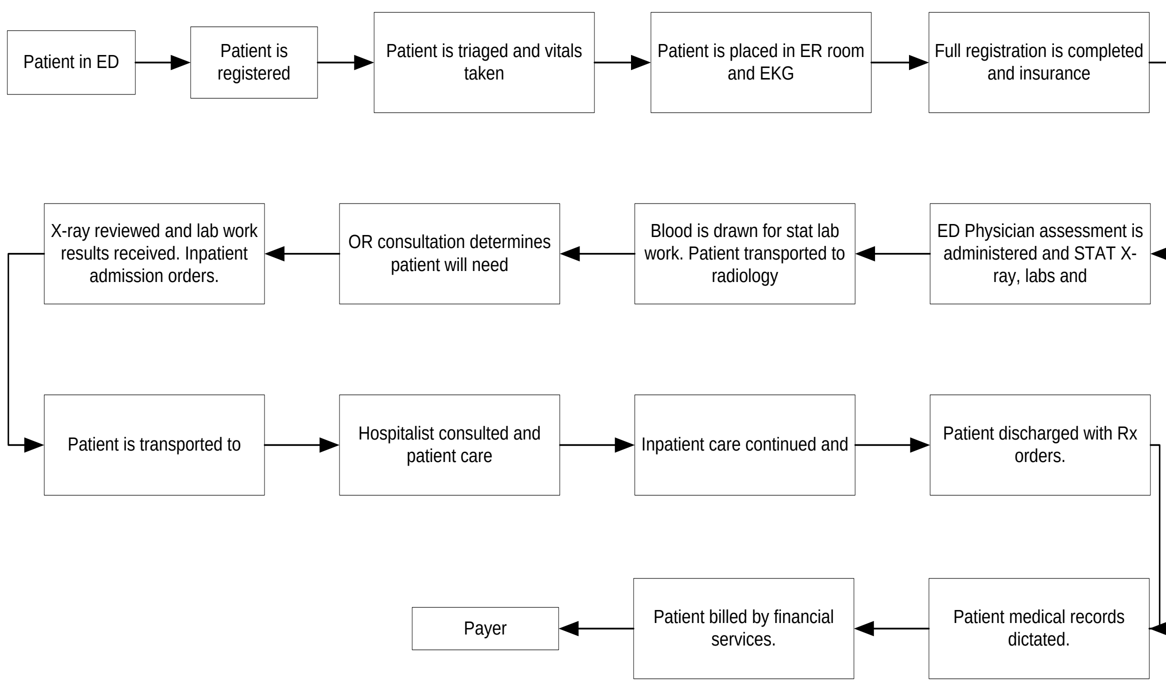

Figure 5: Patient flow ED through surgical services to inpatient and discharge

Figure 6 shows the overlay of patient flow with the care transitions and the corresponding workforce. The best-of-breed technology strategy, inherent in healthcare is indicated by the variety of technologies used by each of these specialties. This workflow shows the technology options available and is typical of any given hospital system that subscribes to the best-of-breed strategy.

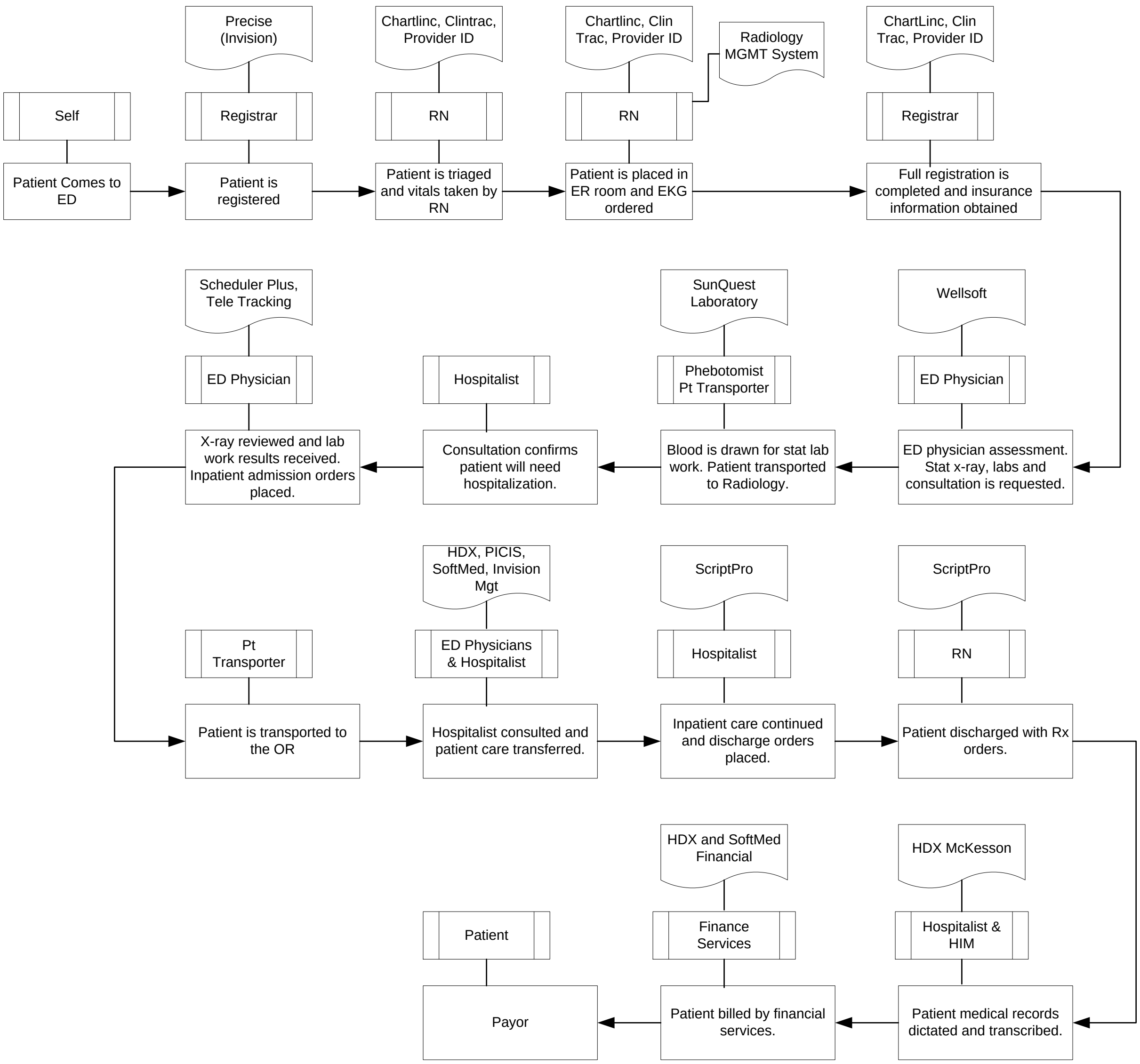

Figure 6: Care continuum and technology interaction

Building ontology for any information source is both technically challenging and, in many scenarios, extremely complicated. Healthcare is especially challenging due to the lack of common standards despite frameworks for data interoperability in healthcare environment [45].

The common perception is that ontology development from databases is the only way to develop interoperability [45]. This research, as described with figures 4 and 5 demonstrates that ontology needs to look at this as a system rather than just a technology. While ontology in healthcare has been focused on specific problems like effectiveness of IT during an emergency [39] or to predict semantic duplicates [46], the purpose of this research is to apply ontology as a method for healthcare design and management from a systems perspective.

3.2 Methodology

The approach looks at healthcare as a continuum and not service line specific. An example of service line specific include systems theories and ontology applied to very specific areas such as emergency departments or surgical services. Nonetheless, while the service line specific approach has been successful, integration and the holistic nature of healthcare requires a global patient view. More importantly, placing patients at the center, and forming the ontology around the patient flow, is a unique contribution of this research methodology. The approach focuses on the healthcare data and the relationship and layering as it relates to patient's experience in healthcare. While the healthcare data domains are well studied and documented [47], this research carries the study into the conceptual, logical and process-based breakdown of the ontology domains in healthcare. Healthcare as a business can be categorized into four key business processes. The business processes are listed below.

1. Patient Care
2. Patient Management
3. Billing and Revenue Management
4. Employee Management

It is important to highlight that these are not clinical processes but rather business processes. Patient care business process defines the services rendered by members of the hospital (clinical or others) to supervise the patient health, manage illness, and preserve/improve health through services. This is primarily a clinical function. Patient management is the behind-the-scenes non-care related activities that support a patients' encounter in the hospital, like patient registration. Billing and revenue management process is responsible for services related to accurate billing. Finally, the employee management process grouping is defined as services that are carried out to manage the information of hospital employees, typically associated with the medical staff office and human resources.

Figure 7 shows the key functions defined under the business processes described above. The depth of each of these process groupings give us a fuller understanding of healthcare as it relates to the patient in addition to the process group itself. As depicted, surgical services (OR Management) and pharmacy are in the continuum rather than as a service line by itself. This breakdown shows the key processes and the functions within those processes that define the care continuum.

3.2.1 Healthcare Data

With a better understanding of the four key processes outlined above, the need to look at the organizational ontology map becomes clearer. Each functional area under the business process is supported by a wide variety of technologies. The patient's interaction with the healthcare continuum for a specific episode of care is defined as the encounter. Each encounter can have multiple functions and processes that cross each other. For example, a patient during any given encounter might have multiple lab and pharmacy orders. As discussed in the previous section, major business processes can be broken down into key functions. Those key functions can be grouped into six major data groupings: Clinical, Ambulatory, Financial, Operational, External and Research data.

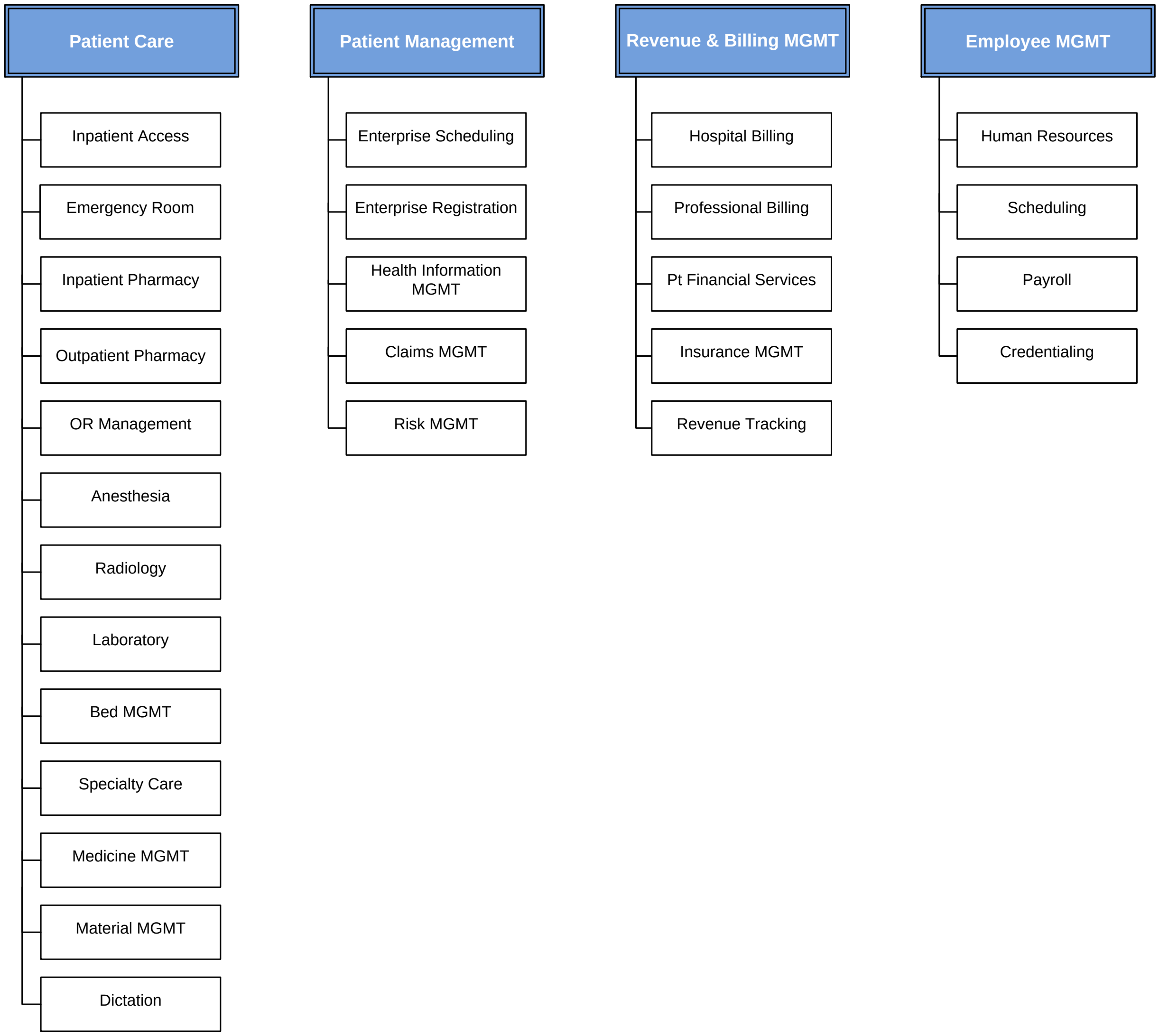

Figure 7: Functions within healthcare process grouping

It is fundamental to breakdown all data groupings before starting to define healthcare data. Patients cut through all the services, functions, processes and data groupings. Seamless integration will result in better experience and outcomes for the patient. The idea is to understand the ontology of all the data with the patient in the center, rather than the process or function. Best of breed technology was built with the function/process as the central of the healthcare continuum and as we break down silos, it is important to have a patient centric view to understand and appreciate the overall complexity of the care coordination within the healthcare system. Figure 8 shows the operational break down of the six major data groupings that revolve around the patient and the encounter.

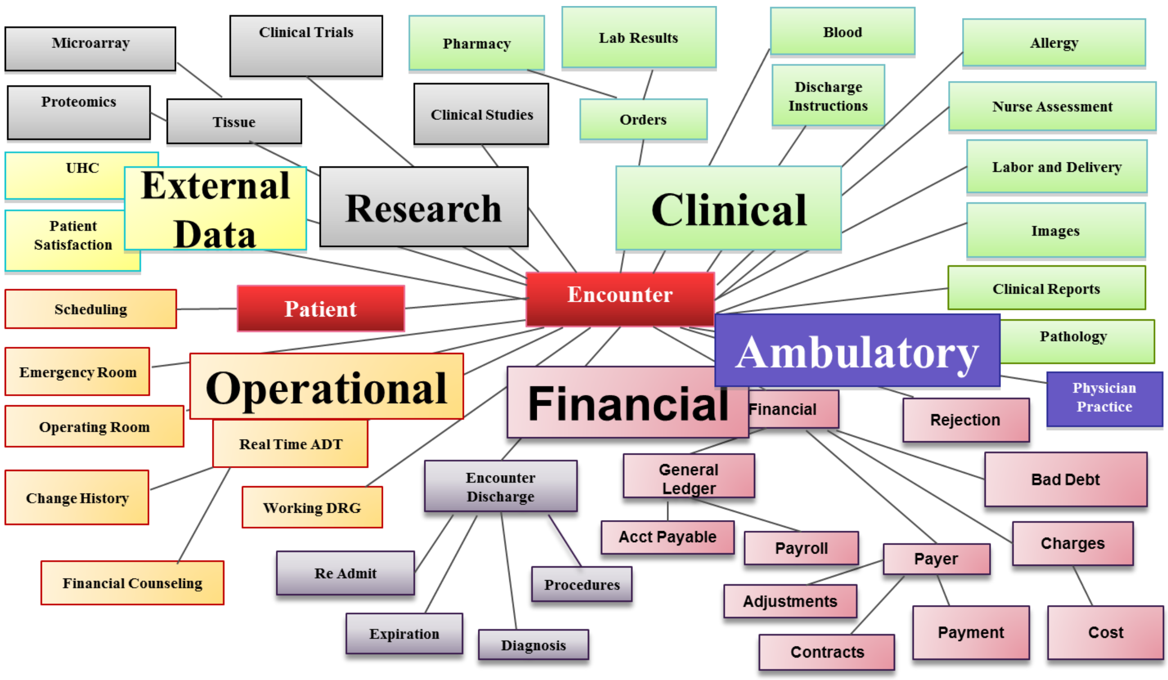

Figure 8: Healthcare functional ontology

3.2.2 Relationships and Layering

With an understanding of healthcare data business groupings the following section focuses on building the relationships and layering that will help with rebuild data relationships. While this is no different than the concept of building a data warehouse, research shows that data stored for business analysis continue to remain separate from the operational layer, leading to no significant improvements even with the evolution of the data warehousing systems [48]. The buildup of relationships and layering will aid in developing procedures in distributed environments and require a reconciliation mechanism that can be used to provide information that are either qualitative or quantitative in nature [49].

While it is natural to start building the abstract data model, it is also important to first identify critical success factors as an objective to the organization's stated mission. Critical success factors identify areas of organizational behavior that are critical for the achievement of strategic goals. With the success factors aligned with the overall strategic mission, the Key Performance Indicators (KPI) should be tied to the tactical layer of the organization. Only then can the operational level data, identified as the transactional data, can be mapped to develop a data model. Figure 9 shows the relationships and layers between the strategic, tactical and operational levels connected by the layering of data. The measures derived in each layers are indicated.

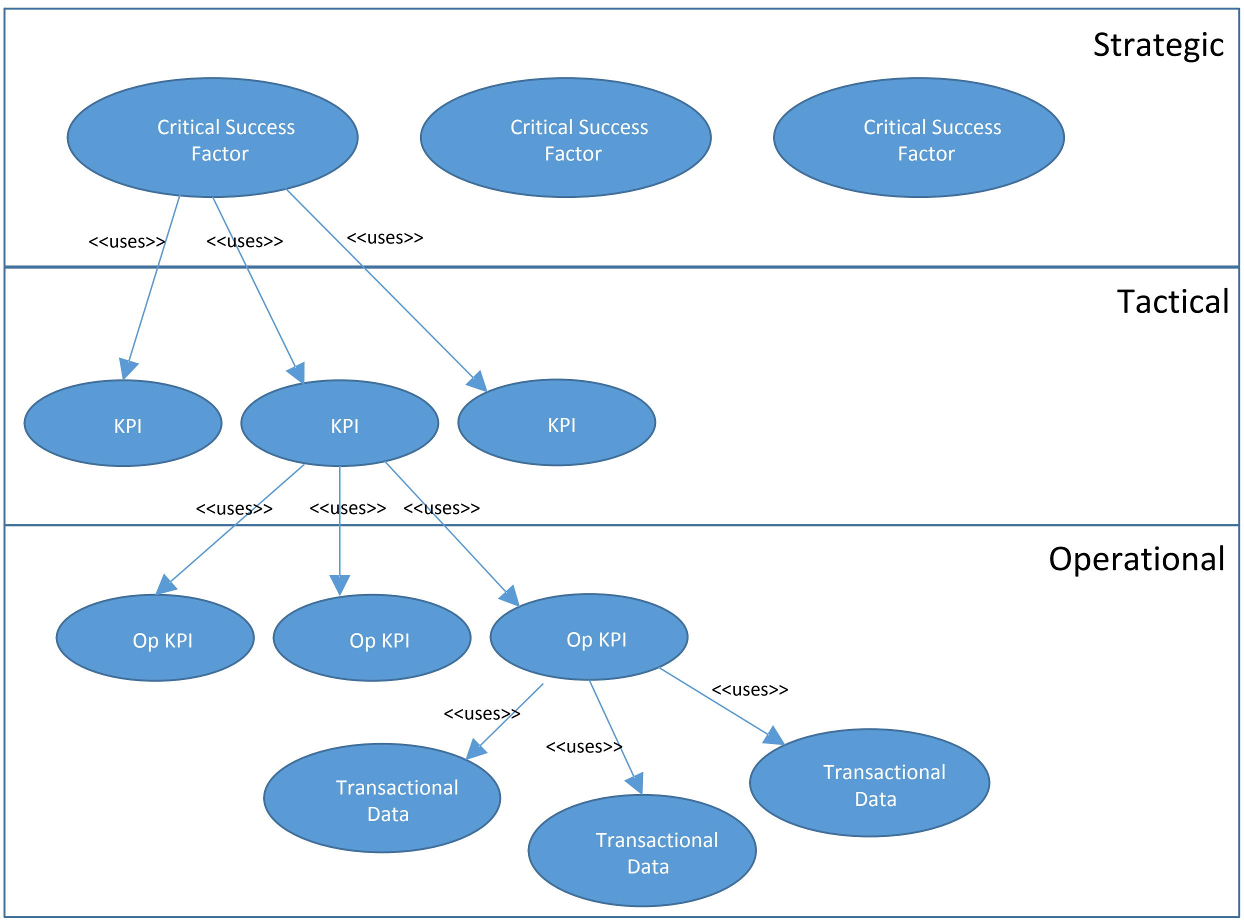

Figure 9: Organizational data relationships and layers

Hospitals select a few critical success factors to focus on at any given time. For example, quality is usually one of the strategic success factors, selected and monitored by and at the highest levels of governance. To expand, applying VBP as one of these critical success factors helps organizations develop tactical key performance indicators. These KPIs are managed by the mid-level management that directly affect the strategic goals. An example of this KPI could be to improve the initial antibiotic administration for community-acquired pneumonia in immunocompetent patients. Once this is set up various operational level KPIs can be developed for bed-side care givers, like tracking each provider and patient to see if the medication was indeed administered. With a breakdown like this, the data needed to track operational and other KPIs all the way to the strategic success factors can be identified which become the building blocks for developing an ontology. As an example, the barcode data generated when the particular antibiotic was administered for a patient, the diagnostic data that says the patient has pneumonia and finally entry that identifies the patient as immunocompetent are all transactional data. This level of organization breakdown helps align transactional data related to process leading to the strategic mission.

3.3 Healthcare Data Ontology Domains

With the alignment of processes, functions and transactional information, it is important to understand the current state of the technology platforms that are set up in a typical hospital. Figure 10 illustrates a cross section of technologies typical to any hospital. It is important to note the cross section of technology, though typical, is only a small fragment of the entire platform. The figure shows an example of a technology stack and depicts how data is extracted from each of these technologies. Data is extracted from these platforms in the form of reports specific to the function or process the specific technology supports. Healthcare is a complex environment with numerous converging services. There are technologies that support all these functions. There are many different technologies that are available for each of these service areas, like electronic medical records (EMR), HR and financial systems. For example, in this Figure 10 Epic represents the EMR system, Kronos the human resource (HR) system, PMM/PFM the financial system, Echo the physician management system and OTTR the transplant system. The figure illustrates the lack of correlation and mapping between different technologies platforms, relating to the lack of patient centric view. Due to the lack of coordination, the source of truth for the patient are not clear and established. The employee record is duplicated in the HR system, EMR and the financial system; and each are independent of the another. This is directly connected to the lack of observability and controllability where the available data is inadequate for improving quality. This illustration depicts why healthcare is in need of a fundamental shift, to improve quality and better meet current and future challenges.

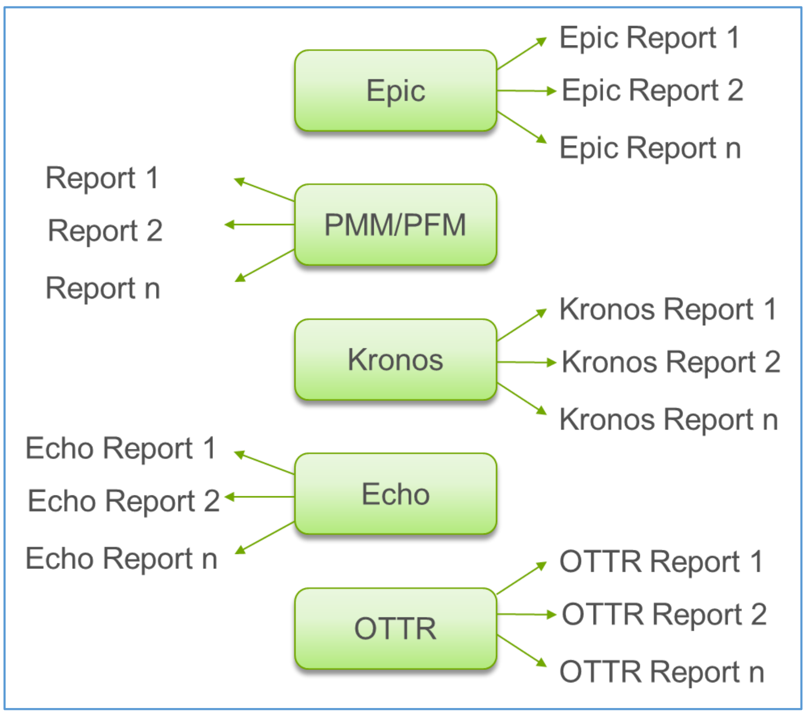

Figure 10: Technology and data relation

For a meaningful correlation of patient centric data, the proposed architecture as shown in figure 11 needs to be developed. This picture shows how the technologies shown in figure 10 can be consolidated into an enterprise data format that is normalized, defined, aggregated and validated to provide the vertical integration required in healthcare. In this example, we see “OTTR” replaced by “Epic Phoenix”, and University Healthcare Consortium (UHC), a new external source, added while the contextual data is kept intact. As discussed in the previous section the two issues that need to be mitigated are 1.) the ability to consolidate (to create source of truth) 2.) the ability to add new data sources. Under this new model, replacement of OTTR with Epic’s Phoenix module allows for consolidation of patient data in the EMR. Adding UHC, which is an external data source that compares and benchmarks data across-hospitals is possible due to the centralization of normalized and defined data elements. This rearrangement and consolidation of information is the fundamental beginning and construction of healthcare ontology.

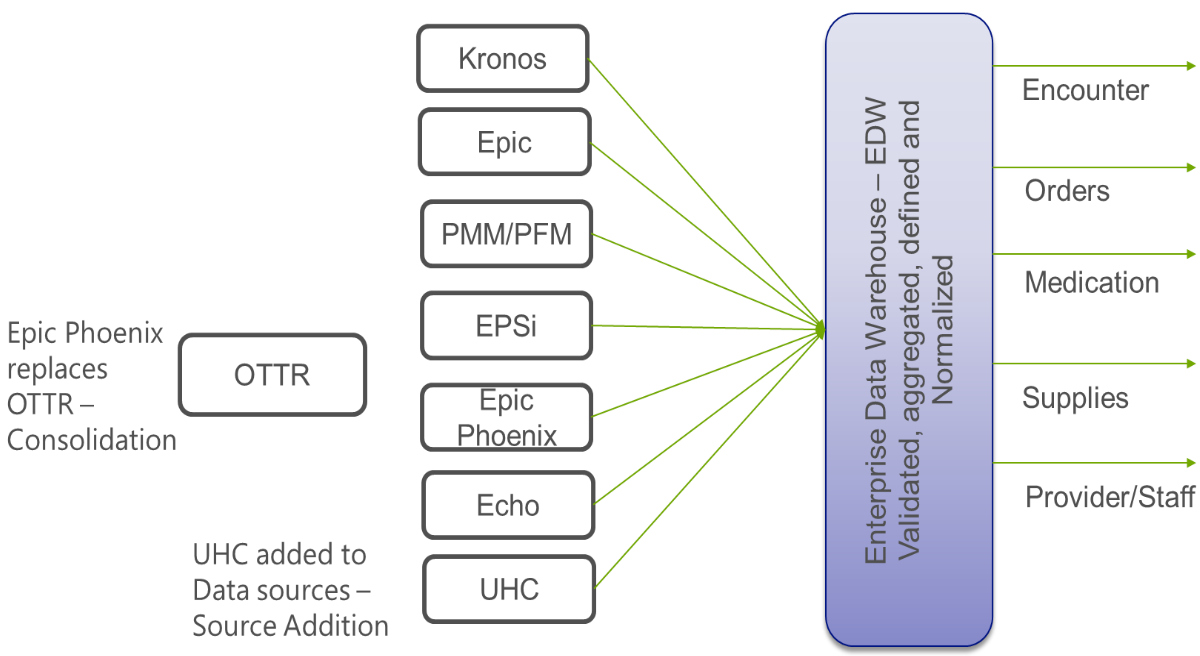

Figure 11: Data consolidation

To better understand the ontology in healthcare, conceptual and logical domains must be defined. Figure 12 shows the architectural view that will allow groupings of technologies into the publisher sources. The other grouping is called the subscribers – the consumers of information. This might contain technologies as well as people that act upon the data. In the middle, Operational Data Store is developed using Extract, Transform and Load (ETL) processes.

The goal is to understand the business processes and how the workflow systems (technology) are built to support the requisite function. To do this we need a conceptual and logical ontology model. Broad business groupings are documented using conceptual models and the detailed, exhaustive requirements are done in the logical layer [50].

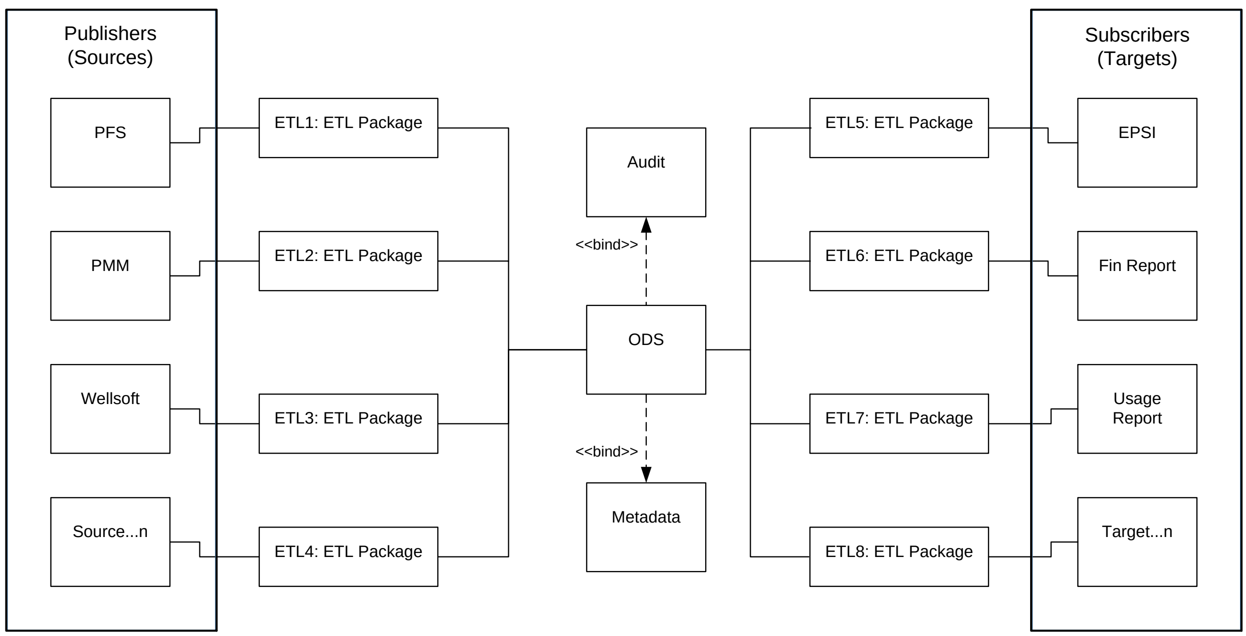

Figure 12: Organizational data store for healthcare

3.3.1 Conceptual

The ontological clarity and stakeholder engagement in the semantics of the domain represented by a conceptual model are cited as the factors that affects the quality of conceptual model [51]. Conceptual data models established using ontology is applied as the framework for developing technology [52], the systemic view is outlined for healthcare in figure 13. This lays out the conceptual domains into the master and transactional data groupings. The affiliate, payer, customer, resources and orders fall under master data information and the financial and encounter data fall under transactional data.

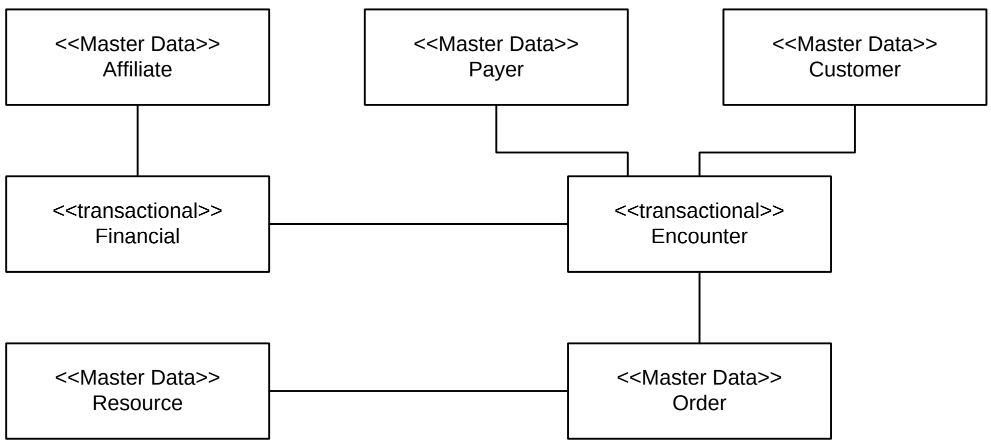

Figure 13: Data domains: Conceptual model

With the highest domains described, the semantic interoperability of the domains can be appreciated by the sub-domain interactions and relationships. The inter-relationships start showing the functional description in healthcare process groupings as shown in figure 14. The affiliate master data domain is now expanded to show the contractor and payroll. With contractors comes invoicing transaction just like payroll being the transactional data for employees associated with the organization. This inter-domain relationship also shows how healthcare services are built around the customers (patients or non-patients).

3.3.2 Logical

Conceptual models can be mapped to their logical representation by further defining the business relationship definitions [53]. The business relationships can be represented by hierarchies to get an abstract view of the relationships [54]. Logical models give us the ability to view data in a heterogeneous environment.

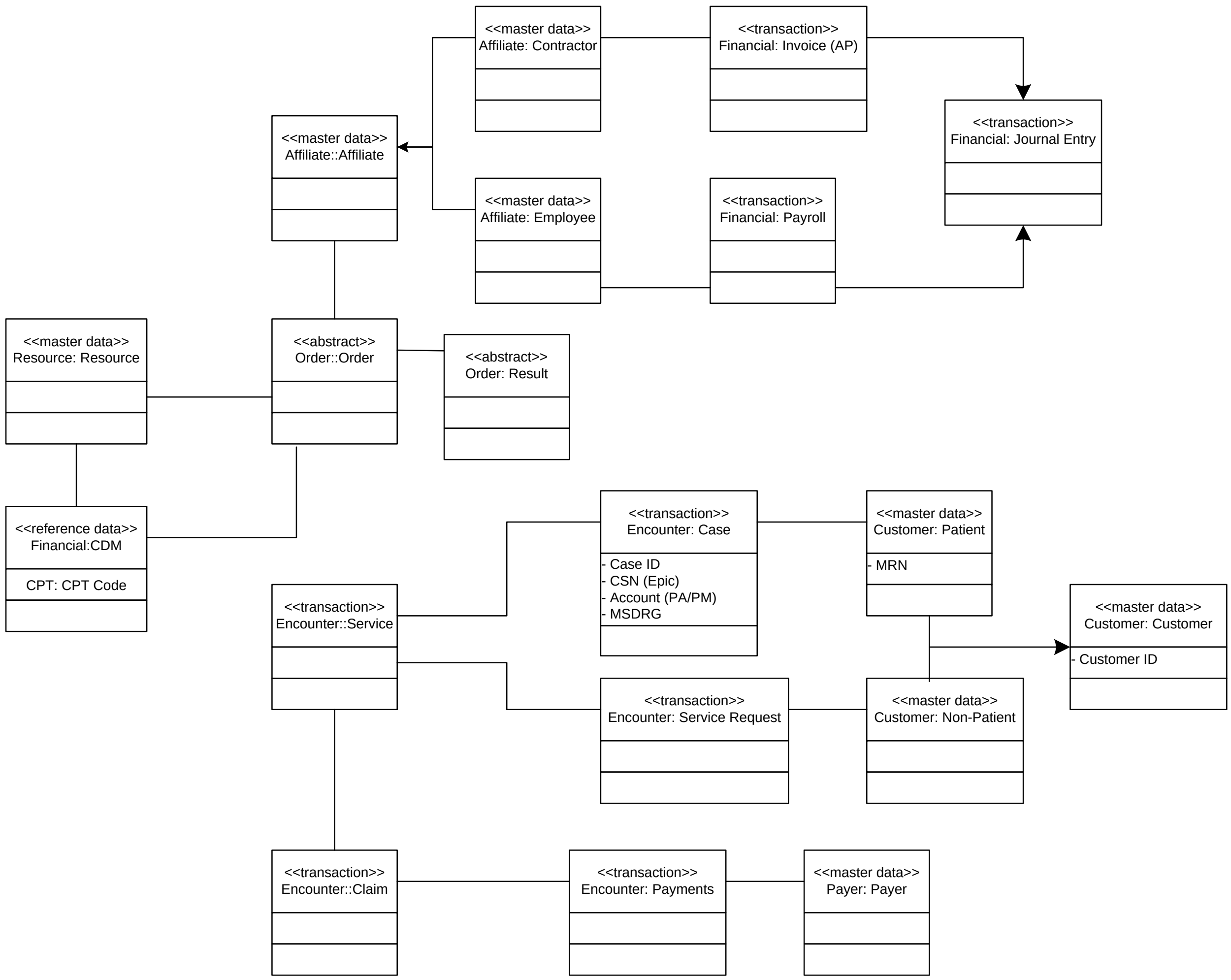

Figure 14: Inter-domain relationships

Domain ontologies' role in establishing conceptual data models [55] is applied to the healthcare system's logical data ontology in figure 15. The logical model shows the resource master data defined under the data domain. This drill down goes into facility, cost center account, subaccount and actively level information. While resource is the master data the logical accumulation of cost center, facilities etc. contribute to the revenue and usage.

This approach of looking at the data ontology facilitates interoperability, ability to share information and service oriented architectures [56].

In addition, a detailed model development allows for time varying and unaccounted attributes [57]. In summary, the patient centric ontology represented by all the functions involved in care allows for interoperability that is uniquely healthcare specific. This ontology-based methodology allows for observation and controllability of a patient's interaction in the continuum within a time invariant system.

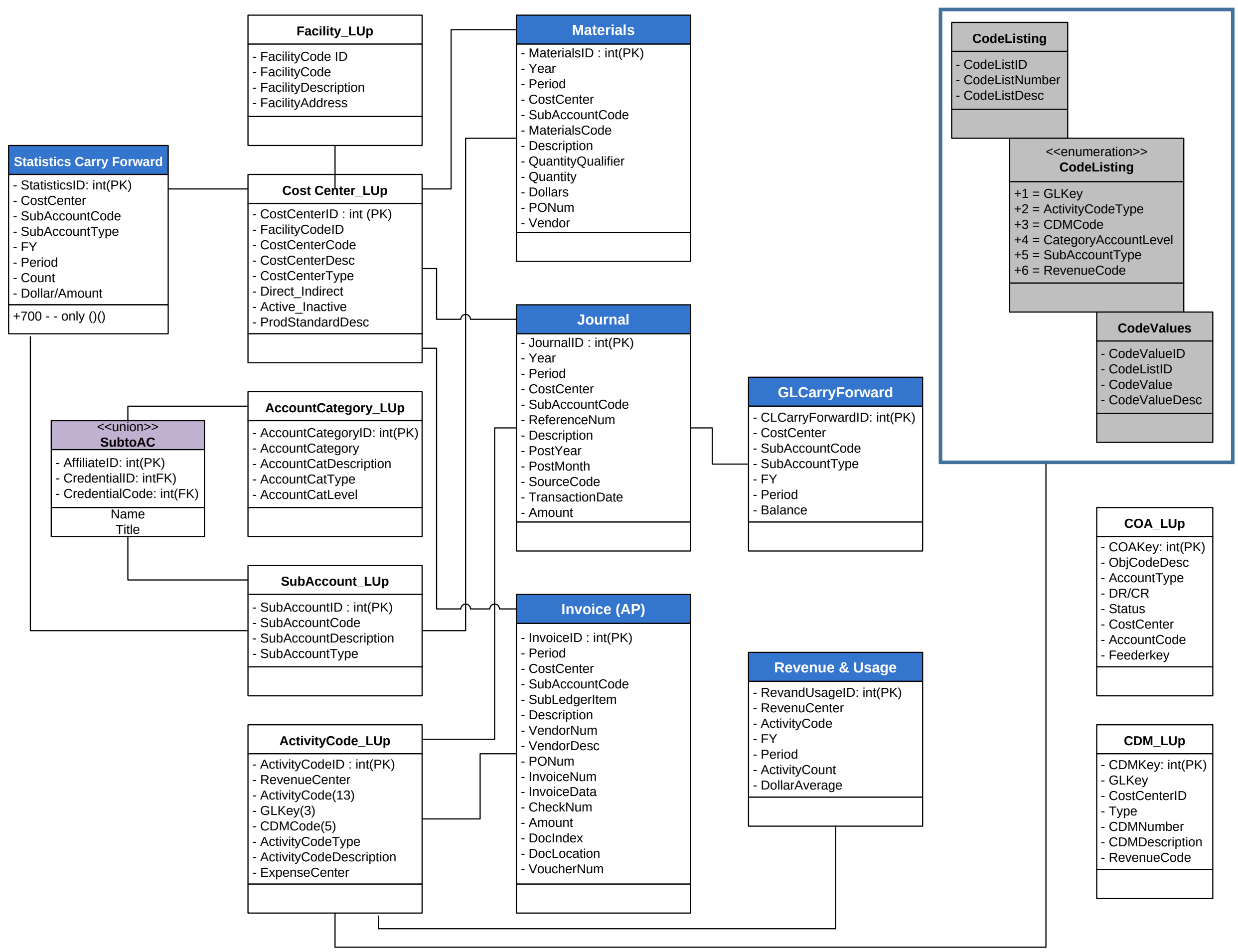

Figure 15: Logical data model

CHAPTER 4: HEALTHCARE ONTOLOGY BASED SYSTEMS ENGINEERING MODEL

The knowledge, relationships, properties and hierarchy between various domains is studied and categorized as ontology [39]. The purpose of this research is two-fold: First: to provide a view of all attributes that make up the functional systems of healthcare, based on ontology. Secondly, use systems engineering methods to design and effectively manage all likely aspects of the systems considered, and to ensure that they are integrated into a whole.

As discussed in the previous chapter, ontology, when applied appropriately, can be used as a methodology to develop a holistic view of healthcare that is today nonexistent. This application of ontology connects strategic outcomes like VBP and quality of care to operational KPIs, to transactional data. This view of transactional data driving strategic outcomes is unique and for the first time gives the complete view of healthcare, rather than service line silos. Application of the conceptual and logical mappings further allows functional mapping that brings together all the functions that take care of the patient in focus, thus making this a patient centric methodology.

While ontology enables data to be applied, it exposes the need for a framework that will need to be followed to manage data. This chapter creates a framework for data lifecycle management and data quality management. Both these lifecycles allows for focusing the massive amount of data that is generated by ontology to achieve specific outcomes. Referring back to figure 4, this methodology is developed to enable specific healthcare outcomes. To perform analytics and to be able to apply appropriate feedback, transaction data will need to defined, mapped and grouped. The need for feedback to identify specific outputs as controls has been well studied and documented in controls theory. As sensors monitor the performance of an engineering plant and measure various data elements, proper feedback from those sensors enable appropriate operation of the plant. In healthcare, there is a lack of "sensors" that send feedback and controls which can be applied to make real time care changes. This chapter applied the following two well-applied principles to develop the framework needed to manage data in healthcare.

1. the mathematical approximation of the physical engineering plant will developed and applied to healthcare as a system. The goal is to fortify the argument that the challenge is identifying the right data elements from ontology to control the system
2. the framework (Software Development Lifecycle (SDLC), V – Model) adaptation to develop a healthcare specific data model. The goal is to demonstrate that application of a systems engineering model in healthcare similar to other industries, such as aerospace, transportation or construction

Based on both these considerations, the data lifecycle emerges. While previous research shows studies identifying the system tools, behavior and properties, it typically stops short of making implementation decisions/ recommendations [58]. This work applies the methodology and framework developed and measures it impacts on quality-of-care improvement. Quality of care has both patient care outcome and financial impact. This section outlines the need for a systems engineering framework that is rooted in data and ontology.

Healthcare quality data are retrospective in nature and, due to the lack of data source consolidation, are driven by manual data extraction and sample reporting to regulatory and reimbursing entities. The result – decision maker are looking at data that is four to six months old; the patient encounter and quality completely unobservable and uncontrollable. Data that is not available during the patient encounter essentially makes the care uncontrollable. The need to have data, while the patient is receiving care is similar to having the pressure and temperature change data in the engineering plant. Knowing these changes enables timely feedback that can be used appropriately to control the system, rather than look at information retrospectively. If a patient is immunocompetent and comes in with pneumonia, it is critical to care for the patient appropriately by administering antibiotics. It is critical that this information is available during the patient encounter, rather than retrospectively. Missing care for a patient like this not only comes with heavy penalties but also results in inappropriate care and is dangerous.

From a systems engineering standpoint, healthcare is a collection of entities that needs to be controlled and observed. This can be accomplished by developing a framework to design a controller and/or compensator to interact with the existing system [59].

Controllability and observability is defined by R. Kalman as:

"*Controllability: In order to be able to do whatever we want with the given dynamic system under control input, the system must be controllable. Observability: In order to see what is going on inside the system under observation, the system must be observable*." [60]

The simple engineering system can be represented as shown in figure 16.

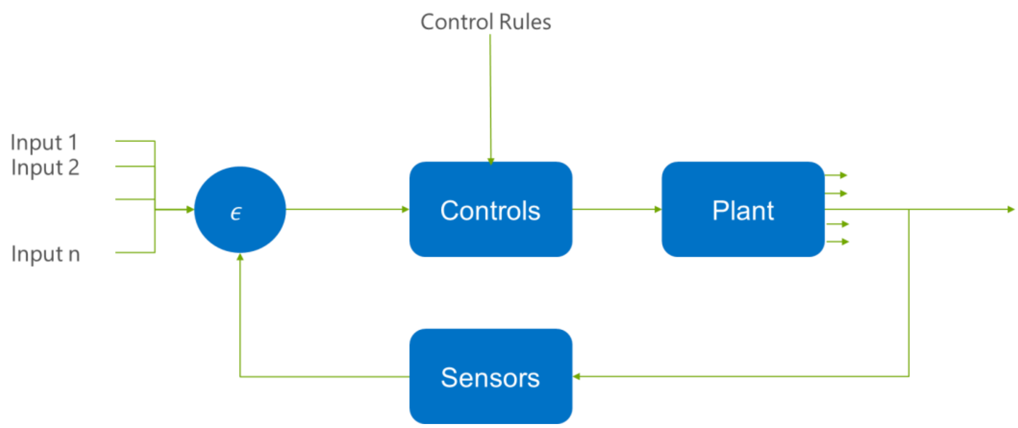

Figure 16: The engineering plant

As depicted, this is a simple system that has controls that take in inputs based on the set of rules and produces the desired output. The output is measured and is returned as feedback to the input, which in turn allows the system to be tweaked to produce the desired output. Figure 17 shows the healthcare system as the plant to depict the similarities in the system.

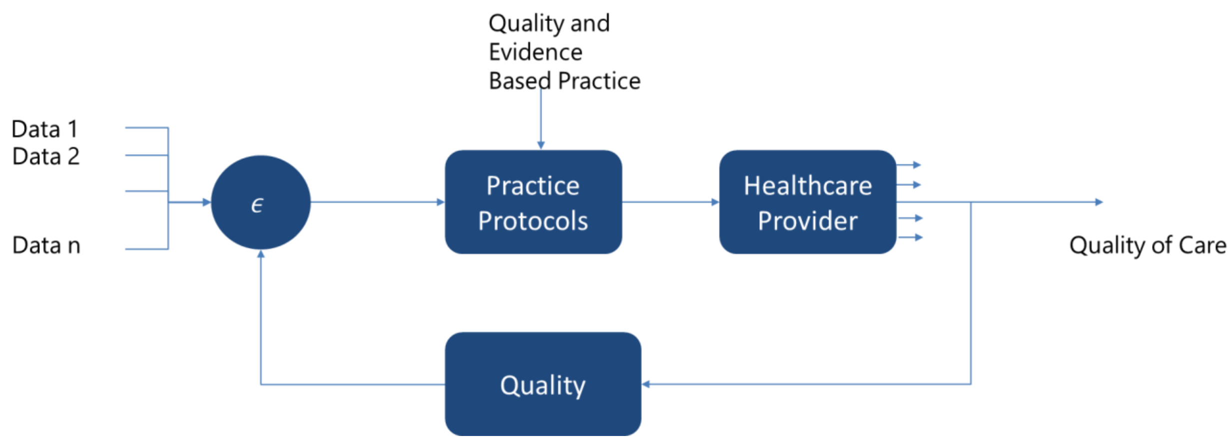

Figure 17: The healthcare system as an engineering plant

Healthcare service is complex, especially due to the human-centered aspects of these systems, creating uncertainties and variables [61] making it complex to model. The data sources created with the various technology sources as seen in the previous chapter is the input for the healthcare system with evidence-based practice as the control rules. Practice protocols and the healthcare provider becomes the system with quality of data becoming the feedback to help change the output, which is the quality of patient care.

This control system can be mathematically deconstructed in simplest terms using the linear discrete-time invariant state variable model. Figure 18 shows such a system that can be mathematically derived to understand system controllability.

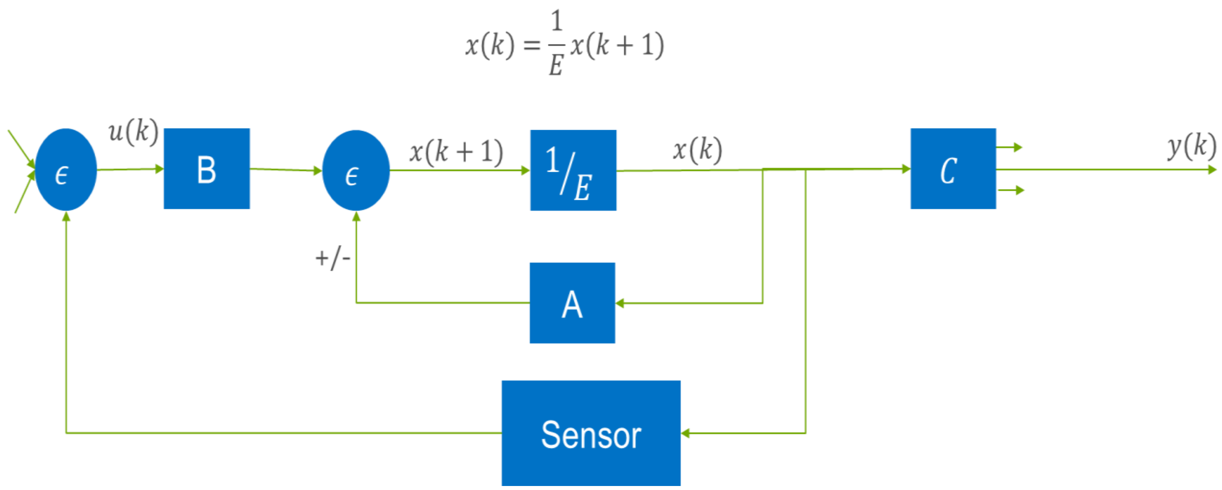

Figure 18: Linear discrete time invariant control system

$$x(k+1) = A_d x(k) + B_d u(k)$$

$$x(0) = x_0$$

$$y(k) = C_d x(k)$$

For the system to be controllable, the desired final state $x(k_1) = x_f$ needs to be attained in a finite time.

While all the care events (example: blood pressure, temperature) count as inputs, the y(k) is defined as the desired output which is the quality of care as a whole will have to controlled within the finite amount of time, which is the encounter. With this basis systemic view of healthcare, it becomes relevant to manage the data using ontology. Since all the data sources control the desired outcome, it is critical the ontology mapping is correct, as described in the previous chapter. This model will need a framework from which the data lifecycle is managed. Data is the raw material for the power plant that is a healthcare system. So, the need to manage the lifecycle of data becomes critical in the design of a system that can change the outcome of patient care.

4.1 Ontology Based Data Lifecycle

Ontology has been developed as a semantic web of machine understandable knowledge, which has been applied for complex distributed manufacturing for cross-enterprise multidisciplinary collaboration [62].

Centralized information management system is critical to set up ontology relationships defined to support systems engineering [63]. The integrated data exchange, the set of relationships and the data library are the basic tenets of an ontology for the quality improvement processes. This will have to be developed and accomplished systematically to support the outcome required. For the data and information sources to be amalgamated, the governance body will need to develop and manage the data life cycle. Software Development Lifecycle (SDLC) and the V-Model are methods used for software development. Data, on the other hand, are not the same as software development. While SDLC and V-model may be applied to the overall governance of the integration and development projects, data requires

1. Manage non-repeatable process
2. Healthcare metric based, which is a biological system by itself
3. Ontology based

Gathering intelligence from the raw data requires an ontological understanding of the system studied. For example, the data governance model is critical to the life cycle, just as a project management office is critical to manage the software development life cycle. The V-model of the Systems Engineering Process is shows in figure 19 as adopted by the Federal Highway Administration (FHWA) in 2005.

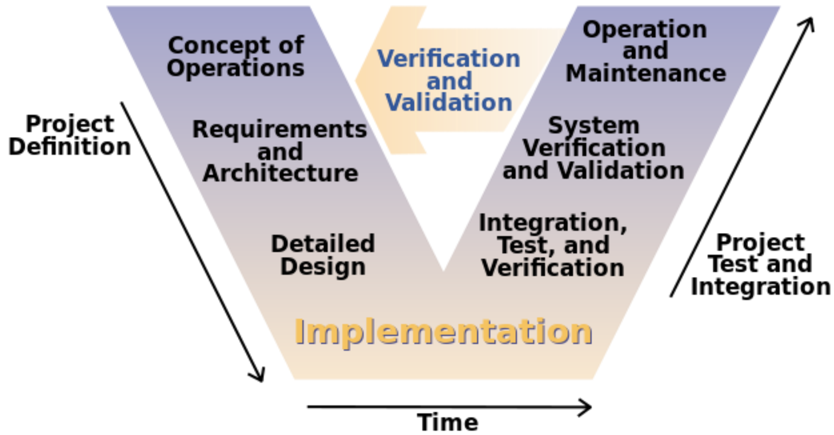

Figure 19: V – Model of the systems engineering process

The simplicity of this model is very similar to the SDLC or any other development model. V – Model visually depicts the need to verify and validate each of the stages. Concept of Operations is verified and validated with the operations and maintenance of the developed product. The same concept applies to ensuring the system operates the way requirements and architecture is managed. Testing is undertaken at the design level, right after implementation. This model has been well adopted in all facets of the modern systems engineering applications from NASA to the Federal Highway Administration.

Developing a data life cycle is central to the data management that can yield the intensity needed to develop an ontology to support the systems engineering framework. This chapter deals with two of the most important aspects of the data ontology

1. Data Lifecycle
2. Data Quality Lifecycle

Both these processes borrow the overall structure of the V-Model and the SDLC model but are uniquely adopted to the healthcare environment by accommodating for

1. Silos within healthcare
2. Lack of technology integration

3. Takes advantage of existing infrastructure and processes
4. Outlines exit criteria for all stages that are healthcare specific – metrics and process

The healthcare data lifecycle can be broken down into 6 major stages. Intake, requirements and design, build, validation, implementation and monitor/control. Each life cycle stage may be further broken down into sub-by process flows when appropriate. Usually a status is generated based on the process flow. There is an associated involvement and responsibility matrix. Finally, there is an exit criteria attached to each of the lifecycle stages. Exit criteria is developed to maintain the integrity of the system where the build is always matched to the requirements and is followed by sign off acceptance. Figure 20 depicts the six healthcare data lifecycle stages.

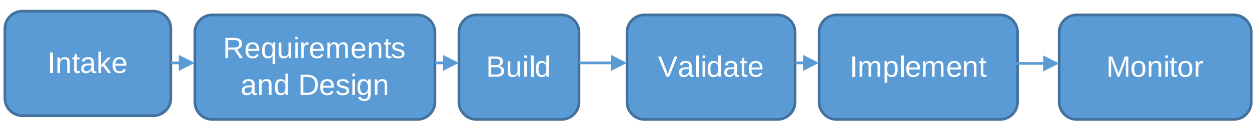

Figure 20: Data lifecycle stages

4.1.1 Intake

Intake is the first lifecycle phase that encompasses two process flows. Initial request for data and high level requirements occurs in this phase. The status is documented once the priority is assigned to a specific data request. A request is submitted in when the data are not already categorized or when requirements are not already completed. End users of the data, also known as customers, are responsible for the request process to be completed before the high level requirements can be gathered. Customers who go through this phase are usually data stewards and/or process owners who are well versed in the data collection that happens. They are also responsible in collecting the high level requirements. Approval of both the priority and the high level requirements are identified as the exit criteria to move to the next stage.

4.1.2 Requirements and Design

Once the intake phase of the lifecycle is complete, it is easy to assign a priority. Unlike the previous phase, the priority of the build is set in this stage. Now a detailed requirements gathering process flow can begin. In this process, both the workflow that affects data collection process and the resources needed are identified and approved. The status is documented with the customer sign off. A best guess estimate for the design, build and validation is provided in this stage. While the data steward is responsible for the detailed workflow and data requirements, the responsibility of the engineer is to get a deeper data ontology understanding. Engineers are also able to assign resources to this effort based on the priority and detailed requirements.

4.1.3 Build

Build is the phase of the lifecycle when both the technology platform (application) and the data ontology is engineered to be presented in a report/dashboard format. In this process flow, the healthcare workflow is studied and data connected to the workflow are identified. Often, there might not be data generated. Thus, this is the stage where new workflows are designed and data fields are mapped. The data integration team is responsible for this stage which is closely based on the requirements from the previous stage. This phase also kicks off the Build Test/Validation process flow, where the workflow and the data mimic the operational workflow. This is the most critical part of this lifecycle. Most importantly, through this phase both the engineering team and the operational team (Nurses, Respiratory Therapists and Physicians) are forced to verify requirements concurrently. It is important to note that the build and the requirements/design phases of the life cycle are iterative.

4.1.4 Validation

This is the final phase before the workflows and processes are implemented. This phase allows the movement of the required data into the production environment. This involves detailing documentation, coding and technical question and answer. The data integration team of engineers are usually responsible for this stage.

4.1.5 Implementation

In this phase, the operational data owners sign off on the final data report, based on all the changes requested. This is also the phase where any data going outside of the organization are validated. That is, the engineers and the customers validate and test reports associated with production data. This phase is iterative with the Build Test/Validation process flow under the build phase of the lifecycle.

4.1.6 Monitor and Control

Once the changes are incorporated and the product is in use, it is imperative to set a threshold to monitor the effectiveness of the process. It is during this phase that the "controllability" of the system is checked to verify if the desired measures are aligned with the process. Workflow changes are also enacted during this lifecycle. During this phase, the end users are trained to appropriately execute on the changes to get the desired outcome. Figure 21 represents all the lifecycle stages along with the process flow, status and the responsibility matrix. This also represents the exit criteria for each of the stages.

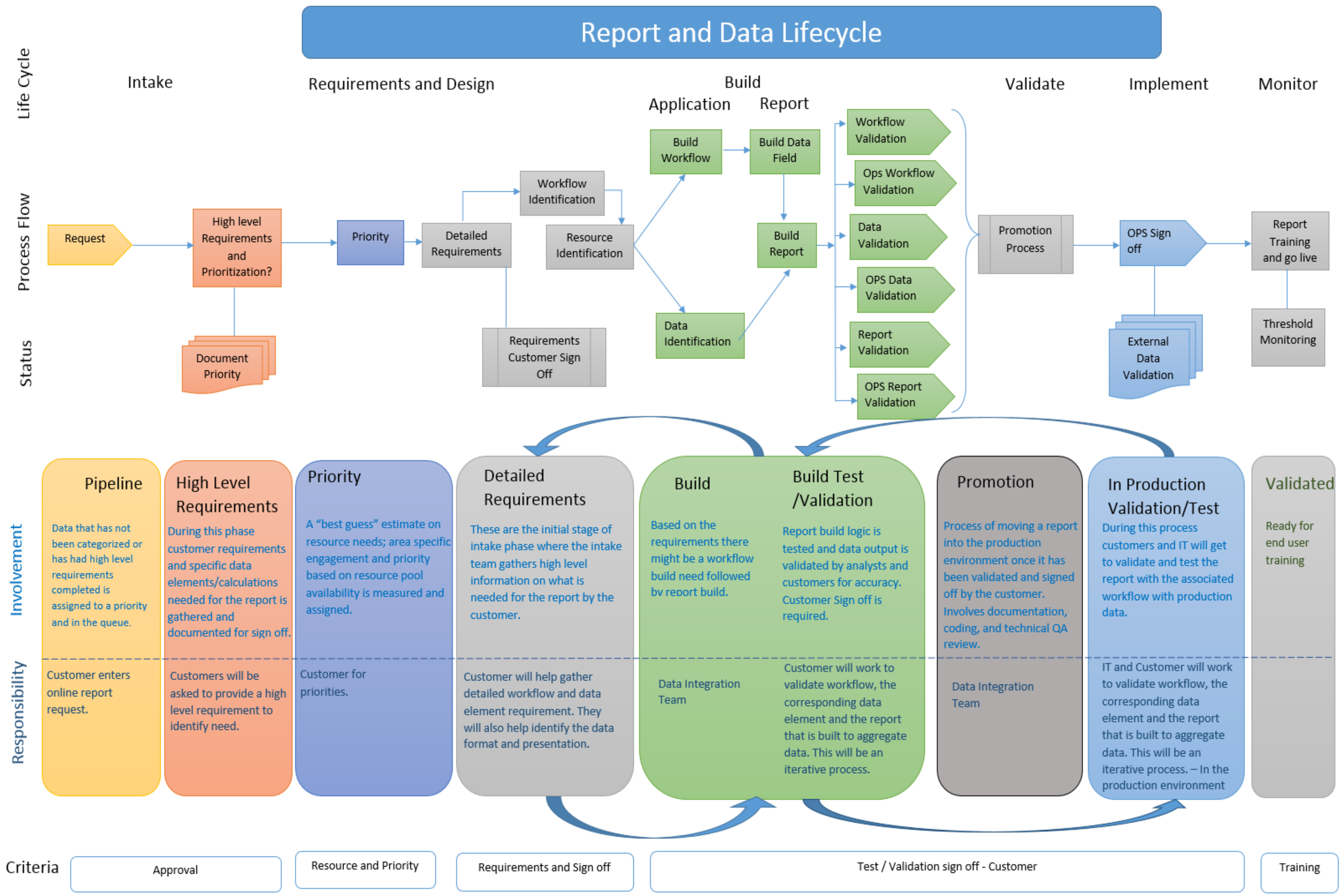

Figure 21: Healthcare data lifecycle

4.2 Data Quality Life Cycle

For the stability of the ontology it is imperative that the quality of the data is clean and complete. Data quality can also be managed as a lifecycle. The lifecycle can be categorized into five stages: standards, source system quality, data cleaning and error checking, testing data validation and finally presentation. Each life cycle stage can be broken down by process flows that are triggered. A deliverable is connected to each of this process flow, followed by the steps associated and the responsibility matrix. Just as described in the previous section there is an exit criteria that is attached to each of the lifecycle stages. Figure 22 shows the six stages of the data quality life cycle.

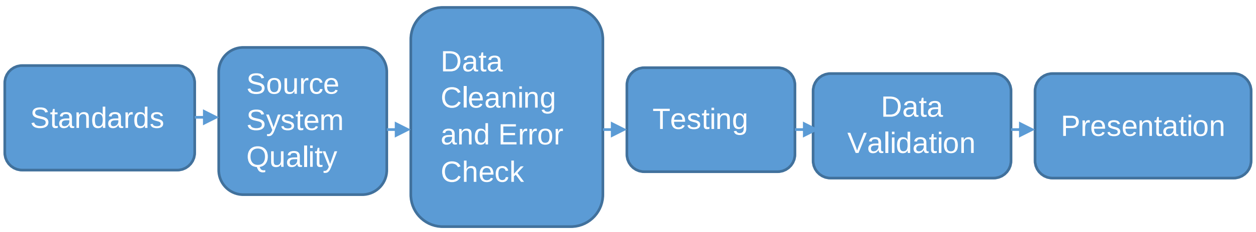

Figure 22: Data quality lifecycle stages

4.2.1 Standards

This is the first phase of the lifecycle where data quality standards are developed. Some of the data quality models already exist and are based on the industry standard, such as definitions around patient observation status and admit status. This is a critical stage as this data element is defined and measured nationally. The deliverable for this stage is a data quality standards document. This phase requires significant literature research to adequately map standards to the business rules associated with the subject area. This is an important stage because new definitions and KPIs are introduced and this stage helps keep the standards document up-to-date with the evolving healthcare environment.

4.2.2 Source System Quality

In this phase, the source system data quality analysis, by data element, using the standards defined during the initial phase, is completed. Not every standard defined in the previous stage has data elements assigned to it. More often than not, data elements are inconsistent and the collection process not accurate. This contributes to inaccuracies and major gaps in data. During this state, the quality of the source data is analyzed and documented. The uniqueness of this model, as described in earlier chapters, is that it allows data to work with existing imperfections. This triggers source system issue resolution and the master data documentation. This stage is critical because not all source systems are clean thus forcing all the issues to be resolved. And not all resolutions allows for a 100% clean up. For example, capturing patients call-light information, can help measure patient satisfaction. But this information is never captured as a transaction. While this might be needed for analysis, proper master data documentation allows for understanding the gap or lack of data. A mapping document and a data dictionary are the deliverables. In this stage, the data elements required for the subject areas are identified along with the source location. This goes through a massive sign off process between the business intelligence analyst and the application analyst and the steering committee that is responsible for a specific business area.

4.2.3 Data Cleaning and Error Checking

This is the most important phase of this life cycle where diagnostic filters for data cleaning, error checking and error event recording is undertaken. Healthcare data is often in multiple sources so this phase makes sure the reference data are correctly sourced and consistent. Columns, structures and business rules are screened. All event errors are resolved along with historical errors are recorded and a single clean file is generated as deliverables.

This is also the phase when broken data links, missing data and format errors are checked and resolved.

4.2.4 Testing and Data Validation

In this phase the testing process is kicked off with the clean data load from the previous stage. Active data is identified and displayed in the presentation layer, dashboards are configured. Any issues with the data at this stage are resolved and the changes are documented. In this phase all data elements in the presentation layer are validated and the security access is set up. Often there are out-of-the-box reports and dashboard that are activated because of the standards that are followed. Testing and validation is completed by issue resolution and documentation.

4.2.5 Presentation

The data quality process is incomplete without process utilization and analytics of data that is the output from the previous phase. Training, certification and analytics happen during this phase. This is the phase where the end users and care providers are able to utilize the data to manage and "control" the outcomes that are expected. Figure 23 shows the Healthcare Data Quality Lifecycle that is uniquely developed as described to support the view of healthcare as a complex system and the ontology to support the system.

Figure 24 shows a characteristics comparison between HOB-SEM and the existing SDLC and V-Models. It is important to notice that the ability to mimic management and biological processes along with supporting ontology is unique to HOB-SEM.

To summarize, the previous chapter demonstrated how ontology enables transactional data to be connected to critical success factors. In this chapter, the ability to manage the influx of data by applying data and quality lifecycles is demonstrated. Together, this forms the Healthcare Ontology Based – Systems Engineering Model.

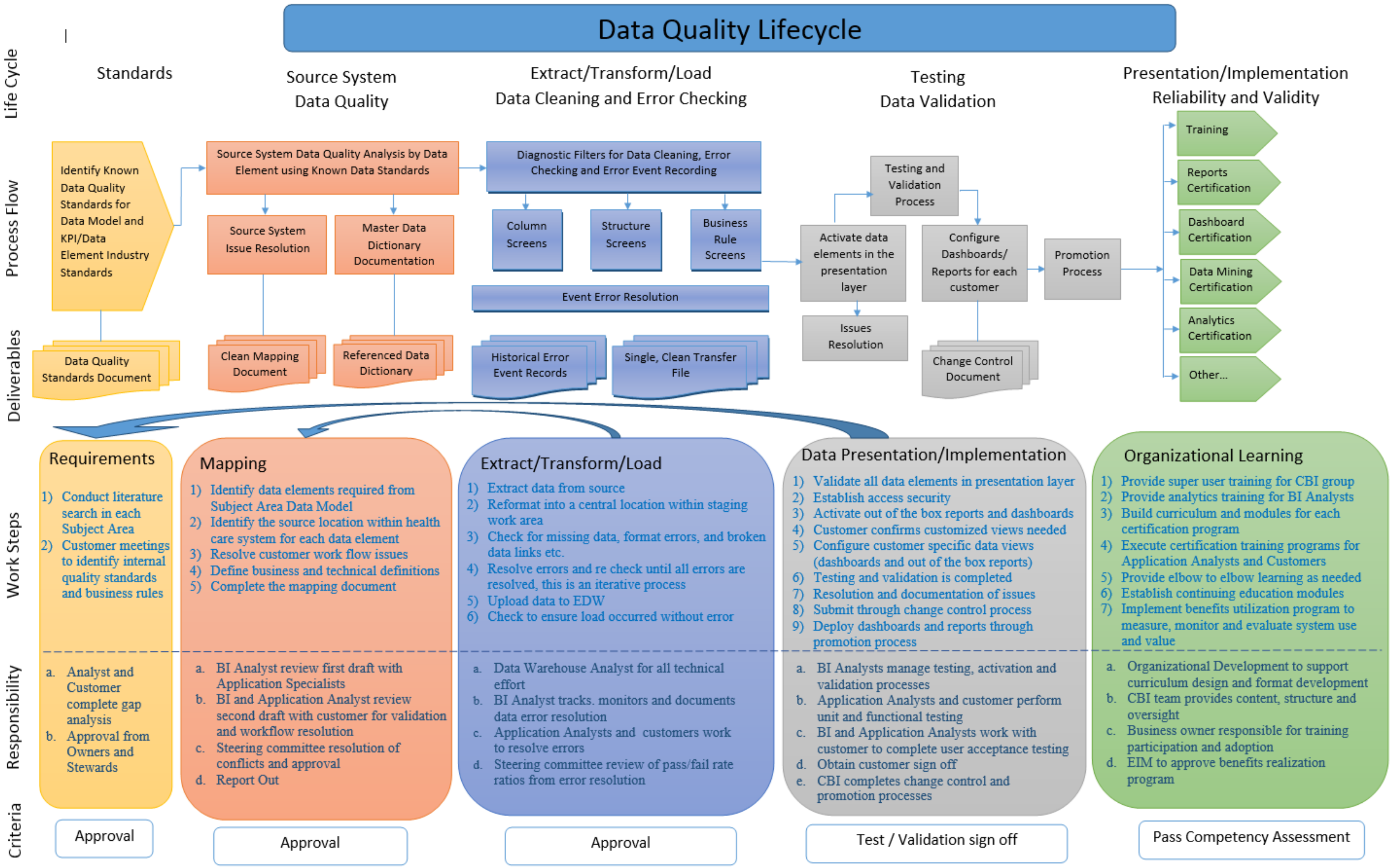

Figure 23: Healthcare data quality lifecycle

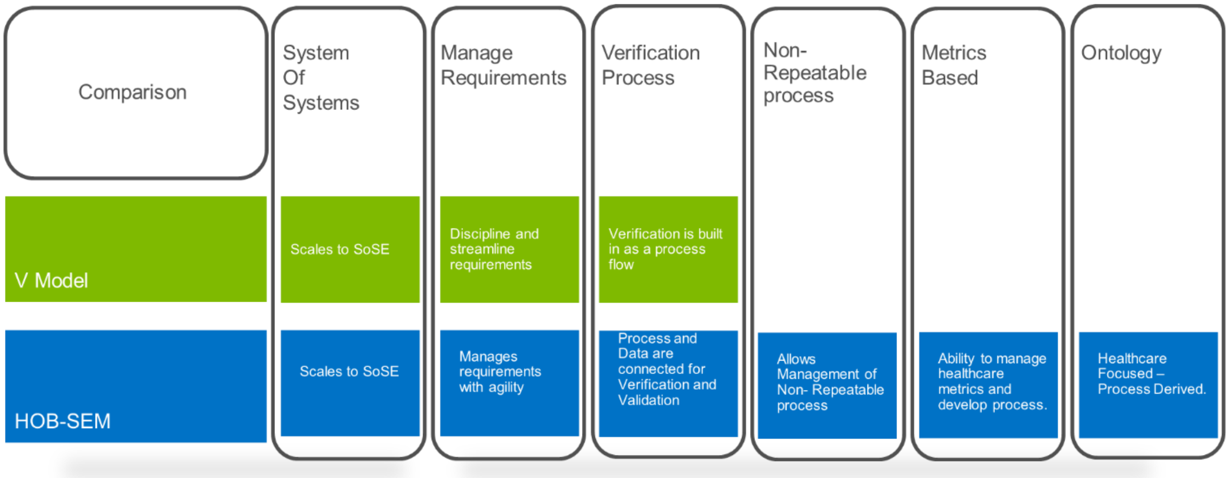

Figure 24: Model comparison

CHAPTER 5: HEALTHCARE APPLICATION

To validate the ontology methodology and the framework to manage the data, in this chapter we apply the Healthcare Ontology Based Systems Engineering Model (HOB-SEM), to issues that persist in healthcare today.

There has been a significant amount of research on data management, ontology and technology and process engineering in healthcare. For example, Ontology has been applied to various facets of healthcare, starting with the applications in IT systems by developing a service oriented architecture (SOA) to manage the healthcare complexity with the help of ontology [41]. Ontology has also been developed to accommodate home based tele-monitoring for certain chronic conditions and patient monitoring for different morbidities through a specific three step ontology [40]. Moreover, a four step process for the design and implementation of a health information system was developed using a hybrid participatory design-grounded theory [39].

However, HOB-SEM is unique in the sense that it allows process ontology to be applied alongside systems engineering for controllability and observability. While ontology can be developed using any of the modalities, methods, and steps described in the literature, the goal is to put a framework around the ontology and data lifecycles to develop a contained system that can be applied to all aspects of healthcare. That is, ontology is used to understand healthcare, while the data lifecycle is developed to give a framework to manage the data of the ontology. This combination becomes a powerful tool that can be adapted to other areas within the healthcare industry.

This section focuses on applying HOB-SEM to an enterprise initiative known as Value Based Purchasing (VBP). Figure 25 justifies the need for a tool like this as it depicts the potential penalty faced by all major hospitals around the country. The three programs that are tested here are: Value Based Purchasing (VBP), Readmissions, and Hospital Acquired Conditions (HAC). As the names imply, Readmissions, meeting certain conditions, after being treated will result in massive penalties. The same applies to HAC, where a penalty is applied to any new health conditions or complications acquired by the patient while in hospital care. Figure 25 shows how the penalties are set to grow up to a cumulative 6% of reimbursement. In 2013, there is a potential 1% penalty for VBP and an additional 1% for readmissions. Over the next few years, readmission penalties are set to increase to 3%. This also gives opportunities, specifically with VBP where there is potential to increase quality outcomes to increase reimbursement by 2%.Therefore, there is incentive to outperform others in all the VBP measures, to take advantage of the potential opportunity.

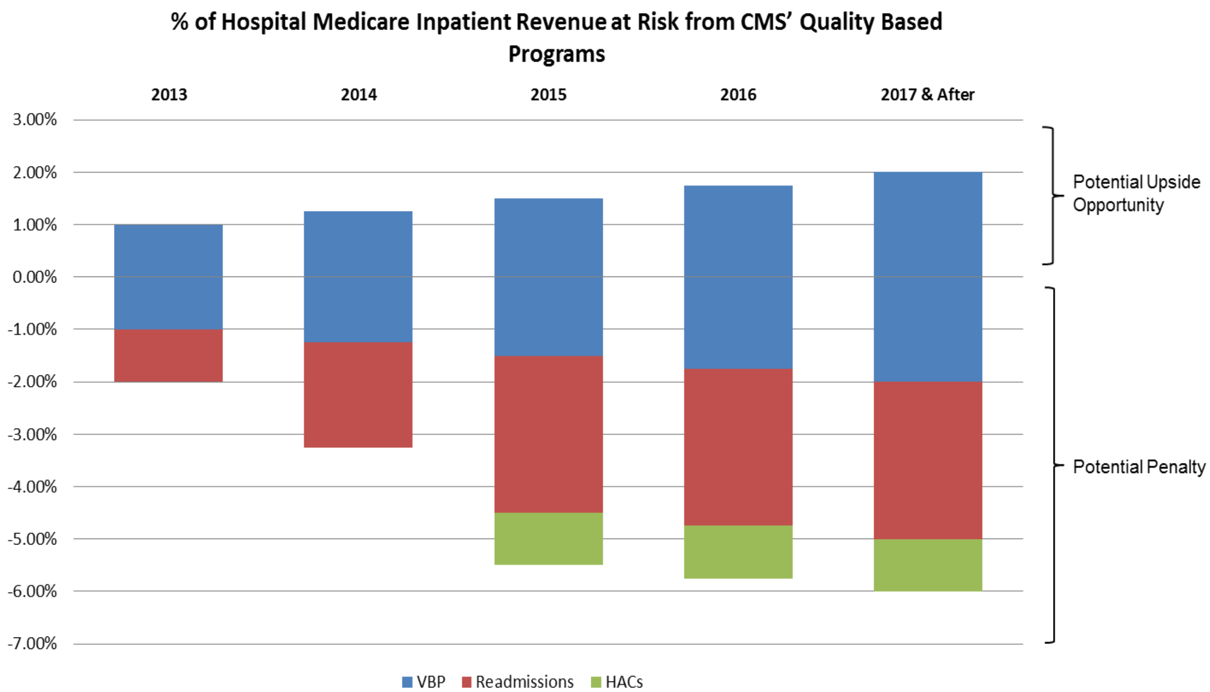

Figure 25: ACA reform: Hospital incentive/penalty model

Since VBP has potential for both penalty and opportunity, the methodology and framework is applied to this initiative. As noted in the introduction chapter, currently the metrics and data for all these measures are completed manually.

For financial year 2014, the clinical process of care measures that are being adopted by CMS are listed in table 3 [14].

Table 3: Clinical process of care measures

Measure ID	**Measure Description**
Acute Myocardial Infarction (AMI)	
AMI-7a	Fibrinolytic Therapy Received Within 30 Minutes of Hospital Arrival
AMI-8a	Primary Percutaneous Coronary Intervention (PCI) Received Within 90 Minutes of Hospital Arrival
Heart Failure (HF)	
HF-1	Discharge Instructions
Pneumonia (PN)	
PN-3b	Blood Cultures Performed in the Emergency Department Prior to Initial Antibiotic Received in Hospital
PN-6	Initial Antibiotic Selection for Community-Acquired Pneumonia (CAP) in Immunocompetent Patient
Healthcare-associated Infections (SCIP = Surgical Care Improvement Project)	
SCIP-Inf-1	Prophylactic Antibiotic Received Within One Hour Prior to Surgical Incision
SCIP-Inf-2	Prophylactic Antibiotic Selection for Surgical Patients
SCIP-Inf-3	Prophylactic Antibiotics Discontinued Within 24 Hours After Surgery End Time
SCIP-Inf-4	Cardiac Surgery Patients with Controlled 6:00 a.m. Postoperative Serum Glucose
Surgeries	
SCIP-Card-2	Surgery Patients on a Beta Blocker Prior to Arrival That Received a Beta Blocker During the Perioperative Period
SCIP-VTE-1	Surgery Patients with Recommended Venous Thromboembolism (VTE) Prophylaxis Ordered
SCIP-VTE-2	Surgery Patients Who Received Appropriate Venous Thromboembolism Prophylaxis Within 24 Hours Prior to Surgery to 24 Hours After Surgery
Survey Measures	
HCAHPS	Hospital Consumer Assessment of Healthcare Providers and Systems Survey

The data elements needed for that computation are obtained from the patient chart, and manually compiled and submitted to a third party organization that validates information and gives the score. The concern with this process is that the charts abstracted are a subset of all the charts, which results in huge assumptions and approximations. Multiple iterations of these data are submitted to a third party compiling agency that in return provides the score to the hospital. This score is reported to the regulatory agency and the reimbursement is determined based on this score. Knowledge of this score has a 4-6 month lag, which does not allow for agile management of the score. This leads to having a score that is not observable and as a result, not controllable.

Currently, data related to these measures such as VBP require the abstractor to review each patient record, manually locating proper evidence to respond to each core measure requirement. Paper forms are filled out, with data such as patient demographics, diagnosis and procedure codes, and drug administration details. After the abstraction of all charts for a given month is completed, subsets of records are selected for a pre- submission clinical review as part of an internal audit process at Reading. This team has the responsibility to participate in these reviews, contributing its expertise and knowledge of the core measure guidelines. Once the clinical review is complete, the abstraction results are manually entered into an error checking process (usually by a vendor software) and submitted to CMS and The Joint Commission. If errors are detected during data entry, the record is sent back to the abstraction team for further review. Additionally, any error found in diagnosis or procedure codes is returned to coding for correction. These modifications can add considerable delay in processing the data for submission.

Applying HOB-SEM will allow quality measures to search through a patient record and automatically extract information specific to core measure reporting. Validation and verification of this will be performed on structured data, such as ICD codes and patient demographics. This model will generate conclusions and provides a pre-defined response to each core measure data element. The goal for this model is to shift the paradigm - freed from the tedious task of manually searching through records to locate relevant information, as the pertinent data is automatically identified by the technology, significantly saving time during data collection. Most importantly hospitals are allowed to apply these resources for concurrent monitoring and improving quality and saving human lives. For the purposes of this study, in the next section, PN – 3b is taken as the performance measure to apply HOB-SEM.

For this study, data from a private not-for-profit hospital with a little over a thousand beds are processed. The hospital is a comprehensive medical facility serving a population of 4 million. In addition, the hospital is a primary teaching affiliate for a College of Medicine with over 300 residents ranging from general internal medicine to neurosurgery. As a level I trauma center, the hospital provides advanced care for the population in the region. This hospital is also the leading organ transplant centers in the country.

5.1 PN – 3b: Measure Details

PN – 3 b is defined as the metric that shows the blood cultures performed in the emergency department prior to receiving initial antibiotic in Hospital [64]. As mentioned earlier, HOB-SEM allows the use of existing processes to be studied and documented and the data lifecycle to receive a state be observed and controlled. For instance, the following figure shows how the pneumonia patients are identified based on diagnostic codes. The blood culture time is collected along with the arrival time. The duration of stay is calculated with the difference between discharge data and arrival data. It is critical to note that the measures can be impacted heavily if invalid data or incomplete antibiotic data is entered. This is the critical reason to study the process to understand the data ontology. The antibiotic administration date that correspond to the initial dose is recorded. Again, data are only valid as long as the antibiotic administration and documentation is complete. Blood culture collection day is calculated by getting the difference between the initial antibiotic data and the initial blood culture collection date. Initial antibiotic time, the timing and the blood culture time are all critical to this process.

Figure 26 shows the work flow in the hospital setting that identifies where the source data is being collected from.

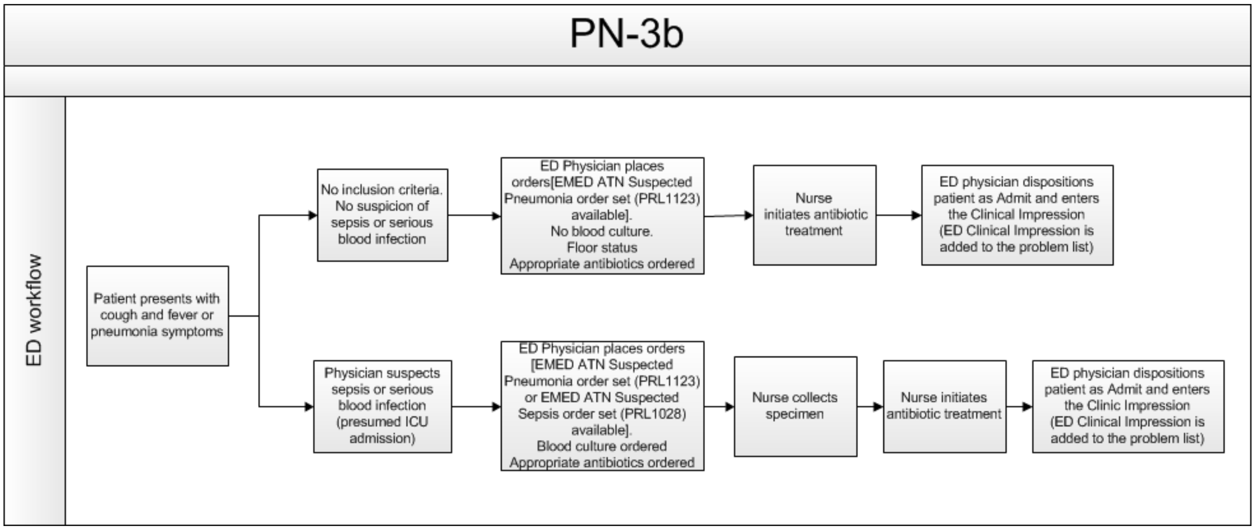

Figure 26: PN – 3b workflow

The process flow classifies the patient as arriving to ED with cough and fever or pneumonia symptoms. The workflow splits when no "inclusion criteria" are found. This is when there is no suspicion of sepsis or serious blood infection, and in that case, the ED physician places a treatment order for a pneumonia order set – a collection of best-practice test and procedures for pneumonia patients. Nurses initiate antibiotic treatment. The ED physician then admits the patient and enters the clinical impression which is added to the patient's problem list.

When the physician does suspect a blood infection, a blood culture is ordered and followed potentially with an antibiotic order. A nurse collects the specimen for the blood culture and then initiates the antibiotic treatment.

Figure 27 shows the pneumonia order set that is used by physicians when they place the orders, as shown in the previous workflow figure. Figure 28 shows the blood culture order that is placed and finally figure 29 shows the antibiotic administration. With a clear understanding of process, this research shows that workflow can be redesigned and redefined to capture all the required data fields for this measure.

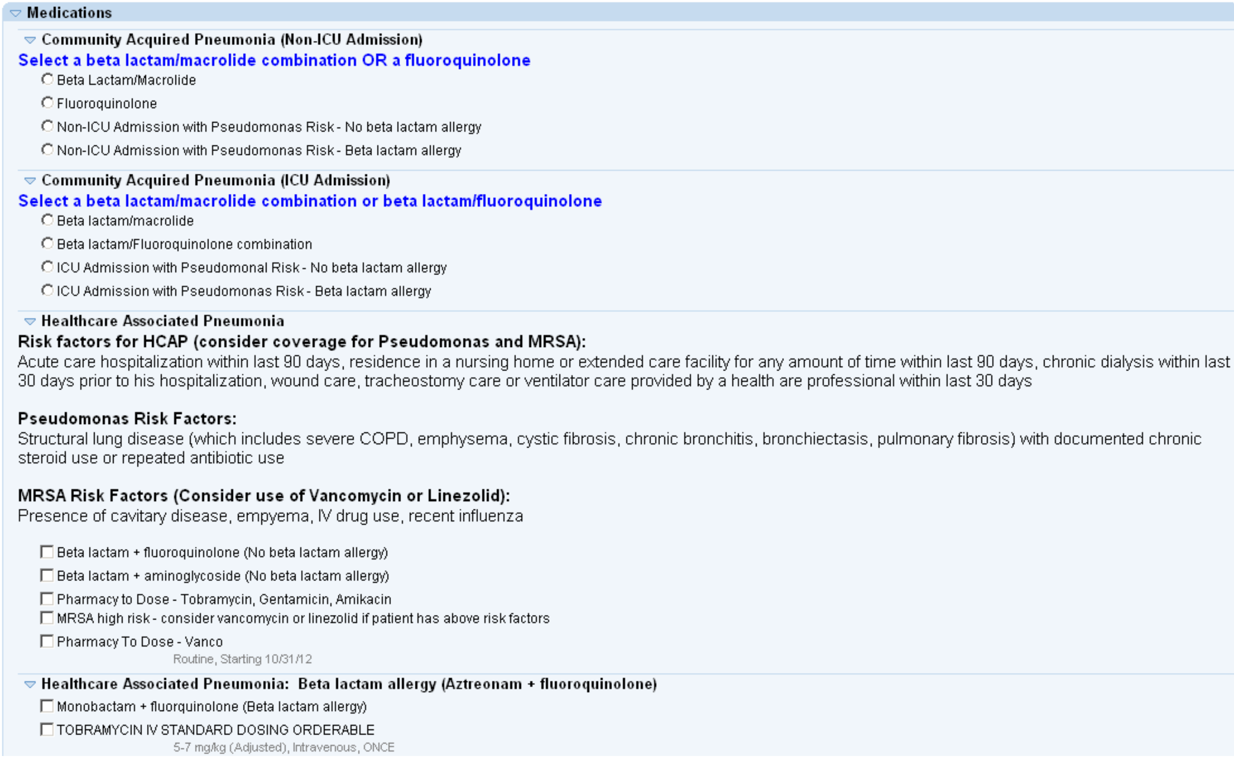

Figure 27: Pneumonia order set

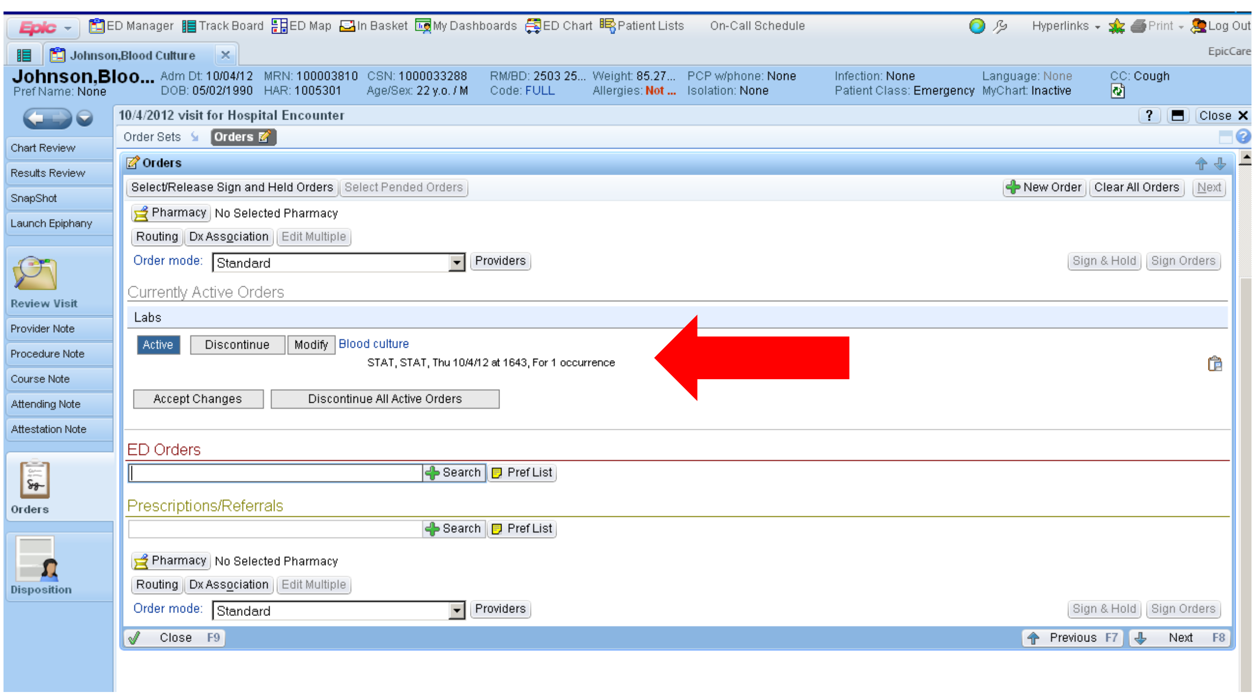

Figure 28: Blood culture order

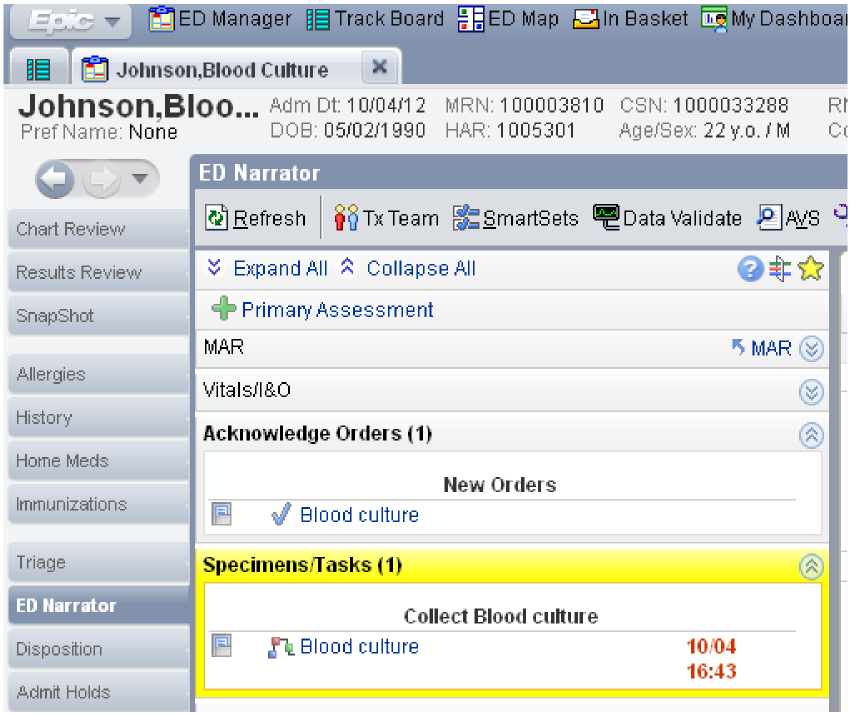

Figure 29: Antibiotic administration

The application of the data lifecycle stages, intake through monitor and control, enables getting information out of the system that can be controlled and tracked.

Table 4: PN – 3b details

Num	Den	UHC Observed Rate (%) - Jan 2013	Num	Den	DASHBOARD Observed Rate (%) – Jan 2013
2	3	66.67%	8	9	89%

PN-3b			UHC results	TGH results	Match?	Reason for discrepancy	Comments
Patient ID	Admission Date	Discharge Date					
xxx	1/13/2013	1/16/2013	PASS (E/Numerator)	NOT ON DASHBOARD (B/Chart Excluded)	No	No positive chest X-ray based on key word search	Positive chest x-ray was found in a later result. Need ability to search all results in a given visit. Investigating feasibility

5.2 PN – 6

To show the effectiveness of the tool, HOB-SEM is applied to PN – 6 which is the Initial Antibiotic Selection for Community-Acquired Pneumonia (CAP) in Immunocompetent Patients. This is defined as the measure of Immunocompetent ICU patients and non-ICU with Community-Acquired Pneumonia who receive an initial antibiotic regimen during the first 24 hours that is consistent with current guidelines. Figure 30 shows the workflow process for this measure.

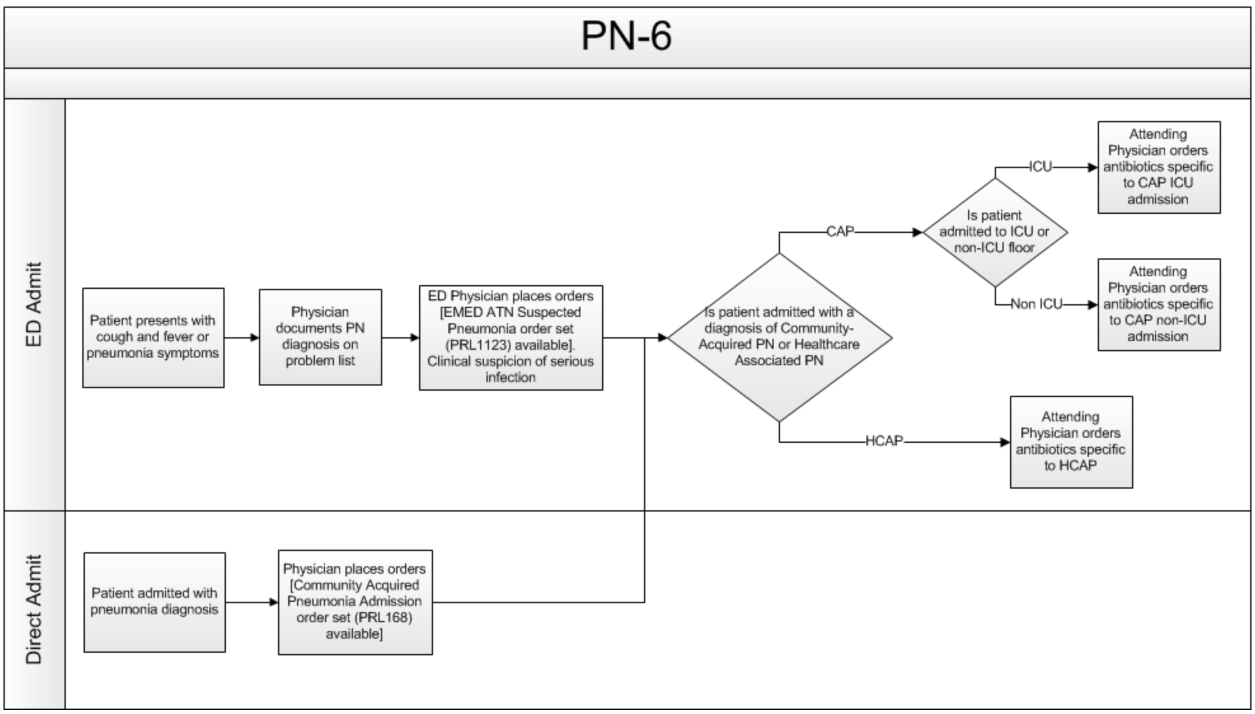

Figure 30: PN – 6 workflow

As figure 30 shows the distinction is made between community acquired pneumonia and healthcare associated pneumonia. Due to the difference in antibiotic administration this distinction is made and treated appropriately. Table 5 below shows how the abstracted data shows 100% compliance with the measure while the dashboard developed puts it at 50% compliance. The reason is that the report could not pick up PN diagnosis in ED or PN was primary reason for inpatient admission. This exposes the lack of data ontology and hence the missing discrete filed to identify this data element.

Table 5: PN – 6 details

Num	Den	UHC Observed Rate (%) - Jan 2013	Num	Den	DASHBOARD Observed Rate (%) – Jan 2013
4	4	100.00%	3	6	50%

PN-6			UHC results	TGH results	Match?	Reason for discrepancy	Comments
Patient ID	Admission Date	Discharge Date					
xxx	1/10/2013	1/18/2013	PASS (E/Numerator)	NOT ON DASHBOARD (B/Chart Excluded)	No	Report could not pick up PN diagnosis in ED or PN was primary reason for inpatient admission	Identify discrete source of ED impression of PN or reason for IP admit
xxx	1/21/2013	1/26/2013	PASS (E/Numerator)	NOT ON DASHBOARD (B/Chart Excluded)	No		
xxx	1/23/2013	1/28/2013	PASS (E/Numerator)	NOT ON DASHBOARD (B/Chart Excluded)	No		
xxx	1/24/2013	1/28/2013	PASS (E/Numerator)	NOT ON DASHBOARD (B/Chart Excluded)	No		

5.3 Results Summary

Table 6 shows the summary of all the relevant VBP measures. As in previous examples, results from the dashboard developed using the HOB-SEM model is compared to the manually extracted data.

Table 6: VBP measures summary

Performance Measure	Num	Den	UHC Observed Rate (%) - Jan 2013	Num	Den	DASHBOARD Observed Rate (%) – Jan 2013	% VAR
PN-3b -- Blood Cultures Performed in the Emergency Department Prior to Initial Antibiotic Received in Hospital	2	3	66.67%	8	9	89%	-22%
PN-6 -- Initial Antibiotic Selection for CAP in Immunocompetent - ICU Patient and NON-ICU Patient	4	4	100.00%	3	6	50%	50%
HF-1 -- Discharge Instructions	18	19	94.74%	63	63	100%	-5%
AMI-8a -- Primary PCI Received Within 90 Minutes of Hospital Arrival	2	2	100.00%	2	3	67%	33%
PN-3b -- Blood Cultures Performed in the Emergency Department Prior to Initial Antibiotic Received in Hospital	2	3	66.67%	8	9	89%	-22%
PN-6 -- Initial Antibiotic Selection for CAP in Immunocompetent - ICU Patient and NON-ICU Patient	4	4	100.00%	3	6	50%	50%
SCIP-Inf-1 -- Prophylactic Antibiotic Received Within One Hour Prior to Surgical Incision	64	67	95.52%	127	135	94%	1%
SCIP-Inf-2 -- Prophylactic Antibiotic Selection for Surgical Patients	64	66	96.97%	150	158	95%	2%
SCIP-Inf-3 -- Prophylactic Antibiotics Discontinued Within 24 Hours After Surgery End Time	61	64	95.31%	107	130	82%	13%
SCIP-Inf-4 -- Cardiac Surgery Patients With Controlled 6 A.M. Postoperative Serum Glucose	16	18	88.89%	22	26	85%	4%
SCIP-Card-2 -- Surgery Patients on Beta Blocker Therapy Prior to Admission Who Received a Beta Blocker During the Perioperative Period	49	49	100.00%	40	57	70%	30%
SCIP-VTE-2 -- Surgery Patients Who Received Appropriate Venous Thromboembolism Prophylaxis Within 24 Hours to Surgery to 24 Hours After Surgery	77	77	100.00%	81	102	79%	21%

Table 7 shows the known cause of variance for all the measures. This is only possible because of the understanding of the workflow and application of the data lifecycle to govern workflow process and data outcomes.

Table 7: Cause of variation

Performance Measure	Data Elements Needed
PN-3b -- Blood Cultures Performed in the Emergency Department Prior to Initial Antibiotic Received in Hospital	Chest X-ray with positive PN Finding Pneumonia Diagnosis: ED/Direct Admit
PN-6 -- Initial Antibiotic Selection for CAP in Immunocompetent	Chest X-ray with positive PN Finding Pseudomonas Risk Another Source Infection Compromised Healthcare Associated PN
HF-1 -- Discharge Instructions	Discharge Instructions Addressing Medications
AMI-8a -- Primary PCI Received Within 90 Minutes of Hospital Arrival	STEMI/LBBB PCI PCI Time Reason for PCI Delay
SCIP-Inf-1 -- Prophylactic Antibiotic Received Within One Hour Prior to Surgical Incision	Infection Prior to Anesthesia
SCIP-Inf-2 -- Prophylactic Antibiotic Selection for Surgical Patients	Infection Prior to Anesthesia
SCIP-Inf-3a -- Prophylactic Antibiotics Discontinued Within 24 Hours After Surgery End Time	Infection Prior to Anesthesia
SCIP-Inf-4 -- Cardiac Surgery Patients With Controlled 6 A.M. Postoperative Serum Glucose	Infection Prior to Anesthesia
SCIP-Card-2 -- Surgery Patients on Beta Blocker Therapy Prior to Admission Who Received a Beta Blocker During the Perioperative Period	Infection Prior to Anesthesia
SCIP-VTE-2 -- Surgery Patients Who Received Appropriate Venous Thromboembolism Prophylaxis Within 24 Hours to Surgery to 24 Hours After Surgery	Preadmission Oral Anticoagulation Therapy

This table demonstrates the observability of the system for the first time in a systematic way. The full value of the model established in this research is the ability to pinpoint and qualify the data elements, data ontology and lack of process that needs to be fulfilled to obtain better results. For example, running through the HOB-SEM has identified the common data elements across all measures such as, Clinical Trial, Comfort Measures, Events or Meds prior to patient arriving to the hospital and consistency in documentation in the established workflows (ex: reason to extend antibiotics).

CHAPTER 6: CONTRIBUTION OF RESEARCH AND FUTURE DIRECTIONS

Healthcare is a discipline that needs a systemic view and to date the technology adaptation has been limited to silo applications. This is recognized by CMS through their measures and metrics and by how much reimbursement emphasis Medicare is placing on those quality of care measures. Without taking the systemic view of the care delivery model, this issue will escalate, creating catastrophic effects that will reverberate throughout the US healthcare system.

6.1 Summary and Conclusion

To summarize, this dissertation provides a unique model that will be the platform to bridge the technology and outcomes gap by

1. developing a model that is systems based to connect outcomes to a data model with feedback to control outcomes
2. developing the verification and validation lifecycle to identify decision gates
3. developing workflows to outcomes and their source ontology hence allowing a controlled and observed system

While the above three are unique contributions towards this dissertation the required outcomes are studied to better understand the ontology of both the healthcare processes and how they are measured, derived and modelled. Though this derivation is well documented, the reconstruction of this with a systemic view allows development of feedback mechanisms that will enable measured efficiencies. These efficiencies can be measured by meeting the established goals and national benchmarks that are published by CMS and other regulatory bodies.

6.2 Future Research Opportunities

This work provides several directions for future research. First, the ability to apply a uniform model that can be globally applied to all healthcare initiatives. While this body of work looked at patients that quality for specific measures that are set by regulatory bodies, this could be applied to other disease states that need to be managed. The following are key promising areas for opportunities.

1. Identifying, mapping and cataloging data ontologies for all silos of healthcare
2. Apply process ontology and map processes using tools like Business Process Management (BPM)
3. Research and map healthcare data ontology to all regulatory measures, for consistency
4. Develop a framework for managing personalized medicine and patient generated data
5. Research to develop a common framework for larger data sets, like genomics

As healthcare enters the information age, the need for interoperability and agility in decision-making becomes critical to the strategic evolution of any organization. This evolution enables an organization to transform itself to unleash the power of information to the edges of the organization, aligning with the principles of Power to the Edge [65]. This research begins to build a platform that allows organizations to extract the full potential of data, information and wisdom. Healthcare is often characterized as a complex environment with unfamiliar and unknown futures. Valuable information based on sound data allows for agility in any uncertain environment by providing resilience and robustness in the system [66].

Ability to apply systems engineering with sound ontology allows for building technologies that can the verified and validated to produce results that can be quantified. As the literature research showed, there is a renewed interest within the research community to focus on the ontology of healthcare. Finally, the methodology presented is shown with respect to disease management, but an immediate extension would be to develop ontology and systems approach to wellness, population management and specifically personalized medicine leading to a bright future for generations to come.

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