Chapter 7
Wrestling with Big Data: How Nurse Leaders Can Engage

Jane Englebright and Edmund Jackson

Abstract The opportunities arising in health systems from the emergence of large-scale clinical data repositories are immense. The application of data science approaches to "big data" is transformational and has the potential to dramatically improve the health and wellbeing of individuals on a national scale. However, although big data science offers great rewards, it has its challenges too. This is no more evident than in nursing where the sheer amount of data flowing through health systems can be overwhelming. Clinical documentation in electronic health records, publically reported quality measures and business intelligence reports are just a few of the many data requirements nurse leaders encounter daily. This chapter describes the challenges nurse leaders face today and discusses strategies that nurse leaders can use to leverage big data to meet the Triple Aim of improving quality, improving the patient experience while reducing cost.

Keywords Nurse executives and big data • Data models • Standardized nursing languages • Nursing and data analytics • Electronic health records • Interoperability

7.1 Introduction

The emergence of large-scale clinical and administrative data repository's, or "big data", has provided nurse leaders tremendous opportunities but in the face of enormous challenges. Today's nurse leaders are literally inundated with data. From clinical documentation in the electronic health record (EHR), to publicly reported outcomes, to business intelligence reports, nurse leaders are awash in a tsunami of

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data. Clearly the success of nurse executives in the future will depend on their ability to manage this tidal wave of data in a way that meets the Triple Aim of improving quality, improving the patient's experience and reducing cost.

To be successful, nurse administrators of the future will need to collaborate with experts in the field of data science, and familiarize themselves with different approaches to analyzing big data. These methods include knowledge discovery through data mining and machine learning: techniques that can identify and categorize patterns in the data and predict events such as stroke, heart failure, falls, pressure ulcers and readmission to the hospital. They can also predict which staffing model is most likely to yield the best outcomes for a specific patient population.

Equally important will be nurse administrator's ability to communicate real time system performance through data visualization dashboards used to report clinical analytics and business intelligence. Fortunately today's health systems are starting to realize the vast opportunities that big data and data science can unlock. This chapter focuses on the state of big data and data science and what is possible related to nursing leadership.

7.2 Defining Big Data and Data Science

The terms big data and data science are often used interchangeably. However, there is a fundamental difference between the two areas. Data Science is an interdisciplinary field that seeks to capture the underlying patterns of large complex data sets and then program these patterns (or algorithms) into computer applications. An example of a computer application using a programmed algorithm is the Modified Early Warning (MEW) system which predicts how quickly a patient experiencing a sudden decline receives clinical care. The algorithm uses six factors to predict a MEWs score: respiratory rate, heart rate, systolic blood pressure, conscious level, temperature, hourly urine output (for previous 2 h) (AHRQ Innovations Exchange Webpage 2016).

Big data refers to data sets too large or complex for traditional data management tools or applications (Big Data 2015). Said another way, big data encompasses a volume, variety, and velocity of data that requires advanced analytic approaches. So, in this chapter, when we refer to big data, we are referring to the combination of structured, semi-structured and unstructured data stores and the special analytic approaches required to harness, to analyze, and to communicate insights from these data. Big data in contrast to data science looks to collect and manage large amounts of varied data to serve large-scale web applications and vast sensor networks.

7.3 Nursing Leader Accountabilities and Challenges

The chief nursing officer is a member of the executive leadership team of the organization. As such, this leader has accountabilities to both the organization and to the profession. At each level of nursing leadership, nurse leaders balance fiduciary and ethical accountabilities to the employer with accountabilities for the professional practice of nursing. This balancing act inevitably leads to some difficult decisions about deployment of scarce or expensive resources, continuing or discontinuing low volume services, or optimizing the model of care delivery to achieve best outcomes at the lowest cost.

7.4 Systems Interoperability

To meet these accountabilities, nurse leaders use data, lots of data, from many different types of data systems. Generally these data systems can be classified as financial, human resources, operational and clinical. Figure 7.1 summarizes the kinds of data nurse leaders frequently use from these different types of data systems.

These systems have varying levels of sophistication within a given organization but typically the systems are not interoperable. This means nurse leaders are often analyzing financial data first, followed by human resource data, then operational data, and finally clinical data. Nurse leaders then manually synthesize these separate analyses to make decisions. Figure 7.1 depicts this process.

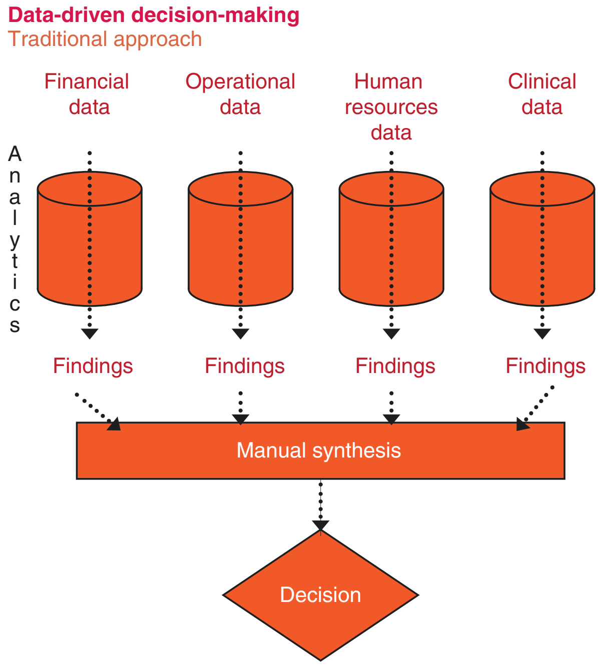

Fig. 7.1 Data-drive decision making: Traditional Approach

7.5 Non-Standardization

To further complicate this traditional approach to data analysis, the data systems may have different data definitions and different time periods that hinder cross-functional analysis. For example, financial systems may be tied to a fiscal calendar with well-defined month-end close activities. Human resource systems may be based on bi-weekly pay periods that do not coincide with the monthly fiscal calendar. Allocating external agency staff hours and costs to the department, shift, and patients across these two data systems for operational or clinical analyses is difficult and may result in different values and conclusions depending on which data source is used. For example, a "day" in the financial system is usually a 24-h period that begins at midnight and ends at 2359 (using the 24-h clock). A "day" in an operational scheduling system is usually defined by shift start and end times. So, the number of patient days or patient encounters in a given department on a specific day may vary, depending on which definition of "day" is used.

7.6 The Invisibility of Nursing

Financial data poses yet another challenge for nursing leaders. While financial information systems are usually the most mature information systems in the organization, nursing financial information is frequently not cataloged in the systems in a manner that enables analysis in relation to patient outcomes, operational changes or specific nurses. Lags in accounting processes for contract labor and lack of alignment with shift times were previously discussed. The inability to assign individual nursing practitioners to individual patients in financial systems is a significant hindrance to understanding the amount of nursing time each patient is consuming and therefore estimating the cost of care for each patient. This type of analysis is important to understanding the value of nursing care.

In addition to these technical challenges, traditional approaches to data analysis have some significant limitations for nurse leaders. Most importantly, these analyses often lack variables that are important to nurse leaders. Variables such as patient care requirements, nurse competence levels, departmental structure and care processes are often the phenomena of most interest to nurse leaders but are not reflected in the traditional data sources in most organizations. Secondly, traditional data sources may not be timely enough to inform operational decision-making. Many traditional data systems produce metrics on biweekly, monthly or quarterly bases. Cross-functional analyses that include clinical outcomes, such as infection rates, may be several months removed from the implementation of the novel clinical process that is being evaluated. Thirdly, many of the variables in the traditional systems are not actionable for the nurse leader. Clinical and human resource metrics calculated at the organizational level, such as pressure ulcer and turnover rates, do not identify the specific departments that need leadership intervention. Finally, the manual nature of the cross-functional analysis may systematically under- or over-estimate the interactions between the variables in the different systems because it relies on the judgment of the nurse leader.

Nurse leaders also expend significant effort helping non-nursing leaders within an organization understand the value of nursing to the organization, in terms of both patient outcomes and financial outcomes. The ability to measure the value of nursing in relation to the outcomes produced and the cost of that production is critical in an era of value-based health care (Pappas 2013). Pappas cites a need for a reporting framework that combines cost and quality as an important first step in documenting the value of nursing to outcomes and error avoidance. Pappas also identifies a need for data that makes tangible some of the intangible work of nursing, such as surveillance. Big data and data science offer techniques for quantifying or datafying and communicating (Mayer-Schonberger and Cukier 2013) concepts that have traditionally been intangible or subjective, giving nurse leaders a new language for expressing the value of nursing to decision-makers at all levels within the organization. These include concepts such as 'complexity of care' when discussing patients or 'novice to expert' when discussing nurses.

7.7 A Common Data Repository Across the System

The chief nursing officer (CNO) role has traditionally been specific to an organization. Thus the data used by the CNO has been confined to data from a single facility. The growth of health systems, and system CNOs (Englebright and Perlin 2008), has created an avenue for aggregating multi-facility data and engaging in big data. The desire to harness the power of big data to answer nursing questions will require nurse leaders within and across organizations to adopt national data standards and to explicitly define data models to generate sharable and comparable data. This is the first for step toward realizing the promise of big data for nursing.

7.8 The Value of Big Data for Nurse Leaders

Clancy and Reed (2015) discuss the data tsunami that is facing nurse executives. Traditional data sources are being supplemented with new data from sensors on equipment, patients and staff within the care environment, with social media interactions, and with retail information. Finding patterns and correlations among these diverse data sources is the province of big data and data science.

Big data and data science promise to answer some of the most perplexing questions facing nursing leaders today. What is the optimal way to organize and staff a patient care service? Big data provides a way to combine large amounts of different types of data to answer complex questions. Traditionally nurse leaders have had to ask financial questions of financial systems, human resource questions of human resource systems, clinical questions of clinical systems, and operational questions of operational systems. Answering these questions for an emergency department would require analyzing volume, payer mix, revenue and cost in the financial system; payroll costs, turnover, skill mix and staff satisfaction in the human resources systems; patient outcomes in clinical systems; and patient arrival patterns and throughput times in operational systems. Nurse leaders are then forced to use their knowledge, experience and intuition to make a judgment on the best way to organize and staff the department. Data science approaches can help by combining large amounts of data from multiple data sources into a coherent analysis and creating predictive models that provide the foundation for evidence based executive decision-making.

Big data and data science would embrace all these traditional data sources but might also include new data sources such as website hits searching for information on flu symptoms during flu season to anticipate a spike in volumes or police reports of accidents near the emergency department. Big data can search for correlations that might not be apparent to nurse leaders, such as the operating hours of nearby businesses. From this data, a model could be derived that predicts patient arrival patterns and care needs. This model could be used for long range planning, but can also be adjusted in near-real time to help the front line manager adjust staffing to be ready to meet the needs of patients that are about to present to the emergency department. This is big data and data science at its best, combining a large volume of highly variable data at high velocity.

7.9 The Journey to Sharable and Comparable Data in Nursing

Sounds almost too good to be true. So, what's the catch? Big data is a group activity and healthcare is still largely an industry of individual or small providers who take great pride in their individuality. To be most effective, big data should rest on a foundation of standardized, coded data elements. SNOMED, LOINC, and ICD10 are well-known data standards in healthcare. However, these taxonomies do not address many of the concepts important to nursing (Rutherford 2008).

Attempts to map the domain of nursing knowledge have been underway for many years. The American Nurses' Association currently recognizes twelve standardized nursing languages, which are summarized in Table 7.1 (American Nurses' Association 2012). The Health Information Technology Standards Panel (HITSP)

Table 7.1 Currently recognized nursing languages

Language	Recognized by ANA
NANDA-Nursing Diagnoses, Definitions, and Classification	1992
Nursing Interventions Classification system (NIC)	1992
Clinical Care Classification system (CCC) formerly Home Health Care Classification system (HHCC)[a]	1992
Omaha system[b]	1992
Nursing Outcomes Classification (NOC)	1997
Nursing Management Minimum Data Set (NMMDS)	1998
PeriOperative Nursing Data Set (PNDS)	1999
SNOMED CT	1999
Nursing Minimum Data Set (NMDS)	1999
International Classification for Nursing Practice (ICNP®)	2000
ABC codes	2000
Logical Observation Identifiers Names and Codes (LOINC®)	2002

Note Adapted from American Nurses' Association (2012). ANA recognized terminologies that support nursing practice. Retrieved March 12, 2016 at: http://www.nursingworld.org/npii/terminologies.htm

[a]Recognized by HITSP in 2007 (Alliance for Nursing Informatics 2007)

[b]Recognized by HITSP in 2008 (personal communication Luann Whittenburg)

recognized two of these terminologies, Clinical Care Classification System (CCC) and the Omaha System, as meeting the criteria required for the harmonization efforts undertaken as a component of the American Recovery and Reinvestment Act and Meaningful Use Electronic Health Record (EHR) Incentive Program (HITSP 2009; CMS 2016).

The goal of the significant investment in health information technology funded by the Health Information Technology for Economic and Clinical Health (HITECH) Act was to create the infrastructure for sharable comparable clinical data that promises to improve care processes and care outcomes (Payne et al. 2015). The detailed data now available in the electronic health record offers the promise for more detailed, more specific and more actionable indicators of nursing effectiveness. However, the ability to apply big data techniques to nursing clinical data is limited by the lack of adoption of standard terminologies that are essential for comparable and sharable data. Currently, there is no requirement that healthcare providers or health information technology vendors use these standardized nursing languages. Adoption is voluntary and uptake has been slow across the industry.

The nursing profession has been working toward shareable and comparable data to describe nursing practice for many years. In 2004, the National Quality Forum endorsed National Voluntary Consensus Standards for Nursing-Sensitive Care; see Table 7.2 (National Quality Forum 2004). This set of 15 voluntary metrics included patient-centered outcome measures, nursing-centered intervention measures, and

Table 7.2 National Quality Forum nurse-sensitive measures

Category	Measure
Patient-centered outcome measures	1. Death among surgical inpatients with treatable serious complications (failure to rescue) 2. Pressure ulcer prevalence 3. Falls prevalence 4. Falls with injury 5. Restraint prevalence (vest and limb only) 6. Urinary catheter-associated urinary tract infection for intensive care unit (ICU) patients 7. Central line catheter-associated blood stream infection rate for ICU and high-risk nursery (HRN) patients 8. Ventilator-associated pneumonia for ICU and HRN patients
Nursing-centered intervention measures	9. Smoking cessation counseling for acute myocardial infarction 10. Smoking cessation counseling for heart failure 11. Smoking cessation counseling for pneumonia
System-centered measures	12. Skill mix (RN, LVN/LPN, UAP and contract) 13. Nursing care hours per patient day (RN, LPN and UAP) 14. Practice Environment Scale—Nursing Work Index 15. Voluntary turnover

Note Adapted from National Quality Forum (2004). National voluntary consensus standards for nursing-sensitive care: an initial performance measure set. Retrieved March 29, 2016 from: https://www.qualityforum.org/Projects/n-r/Nursing-Sensitive_Care_Initial_Measures/Nursing_Sensitive_Care__Initial_Measures.aspx

system-centered measures. These metrics are incorporated into the National Database of Nursing Quality Indicators™ (NDNQI®) (Montalvo 2007) and are considered by the American Nurses Credentialing Corporation (ANCC) in the Magnet Recognition Program®. Over 2000 hospitals participate in NDNQI (Press Ganey 2015), submitting standard data elements, generating benchmarks, and stimulating learning and improvement.

Nurse leaders may be able to learn much about nursing practice from analyzing data from electronic health records. Data generated by nurses comprises a significant portion of the information in the EHR. Yet, most of this data has not been entered into the EHR in a standard format that allows it to be reused, shared, analyzed and compared. Kaiser Permanente and the US Department of Veterans Affairs worked together to compare patient data from the electronic health record related to pressure ulcers (Chow et al. 2015). They created a prototype of a common nursing information model with standard terms that allowed the two organizations to share and compare patient data to improve care coordination and quality of care. The process they used to standardize nursing concepts and assign codes using Clinical LOINC and SNOMED CT was both rigorous and onerous. Chow et al. (2015) cite the challenges of heterogeneous EHR systems, architectural limitations, and lack of data harmonization that were encountered in sharing one clinical data set between two organizations.

Clancy and Reed (2015) highlight the importance of data models in organizing data and standardizing how they relate to one another, how they comport to computer fields within the EHR and how they map to standard nursing terminologies. Data models are the “Rosetta stone” that allows data from distinct systems to be combined for analysis without losing the meaning or context of the original intent or meaning. Data models are particularly important for data originating from clinical documentation due to the variability that exists in both technology and philosophy.

7.10 Gaining Insight from Data in Real Time

While there are amazing insights to gain from EHR data and from clinical measures of nursing performance, the real value of big data comes from sourcing it from multiple systems to address complex questions such as how to operate a nursing service that generates the best patient and staff outcomes at the lowest cost. Big data and data science provide the tools and techniques to bring together large volumes of data from different types of information systems and to analyze it in novel ways that provide insights and support the evidence based decision-making that has been lacking. When you consider the velocity of big data, you create more than understanding or insight; you can create tools that nurse leaders use to manage nursing services in new ways. No longer do nurse administrators need to wait until the end of the month or the end of the quarter to receive time sensitive reports. Today CNO’s are receiving data in near-real time, enabling point of care application of data insights. In other words, nurse leaders at all levels of the organization can use this data, including the charge nurse in the middle of a busy shift. The trick is how to deliver the output to the user within their workflow so that it adds value and does not detract from the important work of taking care of patients.

7.11 Strategies for Moving Forward

In 2013, the University of Minnesota School of Nursing began convening an annual meeting of nurses interested in advancing big data and data science applications within the profession. The participants work collaboratively throughout the year to advance key initiatives related to big data (University of Minnesota 2015). One output of the group in 2015 was The Chief Nurse Executive Big Data Checklist, see Table 7.3 (Englebright and Caspers 2016). The checklist identifies three arenas in which nurse leaders can begin to advance the adoption of big data and data science in nursing.

Table 7.3 The chief nurse executive big data checklist

Create a data culture
Incorporate data-driven decision-making into clinical and operational processes at all levels of the organization
Create continuous, timely feedback loops from data to decision-maker within clinical and operational technologies and processes
Drive access to data to all levels of the organization
Define the nursing terms needed in the existing financial, human resources, operations and clinical data systems
Adopt standard nursing taxonomies to structure and codify nursing terms in each of these data systems to enable internal analysis and external benchmarking • Nursing Minimum Data Set (NMDS) • Nursing Management Minimum Data Set (NMMDS) • American Nurses Association (ANA) recognized clinical terminologies
Collaborate with health care information technology (HIT) professionals to assemble nursing terms from the existing financial, human resources, operational and clinical data systems into a common platform for analysis
Develop data competencies
Secure access to critical informatics and data analytics skills, including statistical analysis, benchmarking, dash boarding and data visualization to realize full benefit of investment in Big Data
Establish the data and informatics competencies required for each nursing role and create a path to achieving those competencies
Create a data infrastructure
Establish a governance structure that includes direct care nurses and is charged with approving changes to the data sources and nursing terms, balancing the benefits and costs of expanding data collection activities
Align the nursing data agenda with the overall informatics strategy for the organization by integrating nursing and informatics professionals into the decision-making committees at all levels
Enforce use of big data, nursing business intelligence and clinical data and, establish data security
Assure that information is integrated across departments/silos, and that data are reliable and consistently used across the enterprise

Note Adapted from Englebright J and Caspers B (2016). The role of the chief nurse executive in the big data revolution. *Nurse Leader.* In Press

7.12 Instilling a Data-Driven Culture Through Team Science

The first arena identified on The Chief Nurse Executive Big Data Checklist is instilling a data-driven culture in the organization (Englebright and Caspers 2016). Nurse leaders do this by embedding data into all decision-making processes in the organization, assuring all levels of leaders have access to data, and that data feedback loops to leaders and staff are timely and transparent. The second arena identified on the checklist is developing competencies for understanding and using big data in self and others. This is a rapidly moving target as big data and data science evolves. The final arena on the checklist is creating the organizational infrastructure that ensures nursing and nursing informatics is an important component of data analytics within the organization.

Nurse leaders must connect to a data team in order to engage in big data and data science. In today's healthcare environment data science is an emerging discipline and hence the question frequently arises as how to form the data team to bring the analytics and technical aspects of this work to fruition. Data scientists are, to read the literature, unicorns, and competition for such talent is fierce. We have found that instead of trying to hire data scientists, it is more fruitful to grow a team.

A critical aspect is to realize that data science or advanced data analytics is distinct from informatics or information technology, it is increasingly part of the operations of the organization. The complexity of the big data and data science questions asked by the leaders of the organization require frequent iteration with the data science team. The necessary players on the data science team starts with a leader who can interact credibly and communicate clearly with both the organizational leadership and the analytical team. That team is composed of nursing domain experts, software developers, user interface specialists, business intelligence developers, statisticians and machine learning experts. They interact with a technical team in information technology (IT) comprised of database architects and engineers, big data architects and engineers, software developers, extract-transform-load (ETL) engineers, testers, and product support. The key for success amid this complexity is communication and teamwork: and like nursing, data science is a team sport.

7.13 Putting It All Together: An Example

This example illustrates how big data and data science can be applied to drive improved performance on inpatient nursing units. This example shows a progression from descriptive analytics (what happened), through diagnostic analytics (why did it happen), to predictive analytics (what will happen next) and finally to prescriptive analytics (what should I do about it).

A nursing unit is a highly dynamic and complex environment and managing this requires a holistic picture encompassing the most important variables from financial, human resources, operational and clinical domains of performance. The question is which are the most important variables?

7.13.1 Step 1: Diagnostic Analytics

This project began with a key user analysis in the patient experience domain, identifying those variables correlated, and causative, with high "Willingness to Recommend" and "Overall Patient Satisfaction" scores on patient experience surveys. One theme that emerged was the management of pain. Diagnostic analytics revealed that patients who reported better experiences with pain management had the highest scores on Willingness to Recommend and Overall Satisfaction. This led to the development of indicators of effective pain management practices that could be incorporated into the unit-based dashboard or data portal. A subset of patient experience scores includes patients with catheter associated urinary tract infections.

7.13.2 Step 2: Diagnostic Analytics

Catheter associated urinary tract infections (CAUTI) are an important, nurse sensitive, measure of clinical quality. In creating a dashboard one might be tempted to display the CAUTI rate in the clinical domain. This is valuable, but is not only in arrears, and *a-definitio,* unmanageable (the event has already happened) it is also difficult to attribute to a specific unit or nurse as a stimulus for action or improvement. Diagnostic analytics fuses many variables to find the leading variables. Unsurprisingly, the mean indwelling time of urinary catheters on a unit is highly predictive of the CAUTI rate on that unit. So, on a management dashboard we display that mean indwelling time (with navigation down to the details of each catheter and patient) rather than the CAUTI rate. The display of average hours on catheter is both meaningful and actionable for the manager and the nurse and directly correlated to the outcome they are trying to impact, infection rate.

7.13.3 Step 3: Predictive Analytics

The diagnostic analytics revealed that that urinary catheter indwelling time is predictive of CAUTI.

7.13.4 Step 4: Prescriptive Analytics

Now that we know that having a urinary catheter indwelling for more than 24 hours is highly predictive of CAUTI, we can simply create a list each shift, ranking patients with catheters by the length of time the catheter has been present and suggesting which need to be cleaned or removed in the present shift. This is actionable for both the manager and the nurse, providing them with tangible steps to take this shift to improve outcomes by driving down CAUTI rates.

This four-step process was repeated for each domain of performance to create a nursing unit dashboard. Figure 7.2 illustrates the first iteration of the dashboard with three domains of performance, clinical, patient experience, and productivity. Still in development are human resources and financial as well as additional clinical indica-

Financial	Human resources	Operational	Clinical
Volume	Turnover	Nursing hours/ patient day	Pressure ulcer prevalence
Revenue	Skill mix	Discharges before noon	Patient falls with injuries
Supply cost	Percent BSN	Patient wait time	Cather-associated urinary tract infection rate
Labor cost	RN engagement	Follow-up phone call completions	Patient experience

Fig. 7.2 Examples of nursing metrics from each type of data system

tors. By taking the same approach though all domains areas of nursing performance, identifying key driver variables, displaying them in a consistent way, and combining that with action-enabling tools, we create a truly potent data-driven management approach.

Big data and data science provide nurse leaders with data that is timely, consistent and relevant and presented in ways that prompt insight and action. This is the realm of clinical decision support and is the effector arm of big data in the clinical setting. The technical components necessary to acquire, process and deliver analytics in support of Clinical Decision Support are significant, most especially when integrating disparate non-clinical sources. Substantial preparation is necessary to ensure success.

7.14 Conclusions

Big data and big data science are an exciting new frontier for nurse leaders. They offer new tools and techniques for simplifying data-driven decision-making. Nurse leaders operate within a tsunami of data and big data and data science offer strategies for finding the meaningful signals and patterns in the data, allowing the leader to provide focus and direction to the organization with confidence.

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Case Study 7.1: Improving Nursing Care Through the Trinity Health System Data Warehouse

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Abstract This case study describes how Trinity Health, a national health system, uses their data repository to discover how clinical nursing actions contribute to knowledge value and meet the Triple Aim. The design and results of four projects using the Trinity Health Data Repository are discussed and include the following exemplars: Decreasing mortality using Interdisciplinary Plans of Care (IPOC's); Identifying factors that contribute to pressure ulcers; Preventing venous thromboembolism (VTE) with pharmaceutical prophylaxis: Predicting malpractice claims for missed diagnosis in the emergency room.

Keywords Big data • Plans of care • Venous thromboembolism (VTE) • Pressure ulcers • Nursing informatics • Data science • Data warehouse • Knowledge value • Predictive modeling • Algorithms

7.1.1 Introduction

In the acute care setting, nurses have the most direct contact with patients. As a result, nurses provide the majority of the documentation and data regarding patient care within the electronic health record (EHR). The explosion of "big data" tools and concepts allows for the manipulation of electronically stored information to create new nursing knowledge. The generation of new knowledge requires the use of scientific inquiry through the EHR and public health data and emerging methods that are revealed as we understand the multiple uses of big data (Brennan and Bakken 2015). While it is apparent that the primary use of EHRs is clinical documentation, the secondary use of stored EHR data for research has taken on new meaning for transforming the way nursing observations and assessments are translated into large data sets to improve patient care.

Recently, Trinity Health assembled a summit of internal interprofessional thought leaders from around the country to discern what "big data" means to the organization. The overarching findings of the summit were that big data means, "Data working for us and not us working for the data". The group discussed the opportunities to leverage the Trinity Health data warehouse in new ways, regardless of the heterogeneity of its initial form. For example, there are multiple ways blood pressure can be entered into an electronic flowsheet due to the many EHRs and data models within the Trinity Health system. Blood pressure can be represented as a discrete entry for systolic and diastolic blood pressure, or concatenated into one data element such as arterial pressure. Despite the lack of homogeneity, there are numerous questions to be asked. The summit concluded that the value of putting data to work in more meaningful ways would benefit both clinical care and financial outcomes.

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Trinity Health's clinical leadership had a vision to assemble data in a single location to better manage duplication and standardize inputs. Data outputs support the organization when they can be used (with minimal transformation or supplementation) to discover new knowledge about nursing practice, operations and patients. In these case studies, the focus is on the relationship between the role of big data and its impact on patients, clinicians, business and Trinity Health's approach for using data to inform nursing through secondary data analysis.

7.1.2 Trinity Health

Trinity Health was formed in May 2013 when Catholic Health East (CHE) and Trinity Health consolidated to form the second largest Catholic healthcare organization in the United States (Brokel et al. 2006). This consolidation and several recent acquisitions have formed an organization of 91 hospitals in 21 states, 51 home care agencies and hospice locations, 14 PACE locations, and 61 continuing care facilities. Trinity Health staffs 3900 employed physicians, 23,900 affiliated physicians and greater than 35,000 registered nurses (see Fig. 7.1.1).

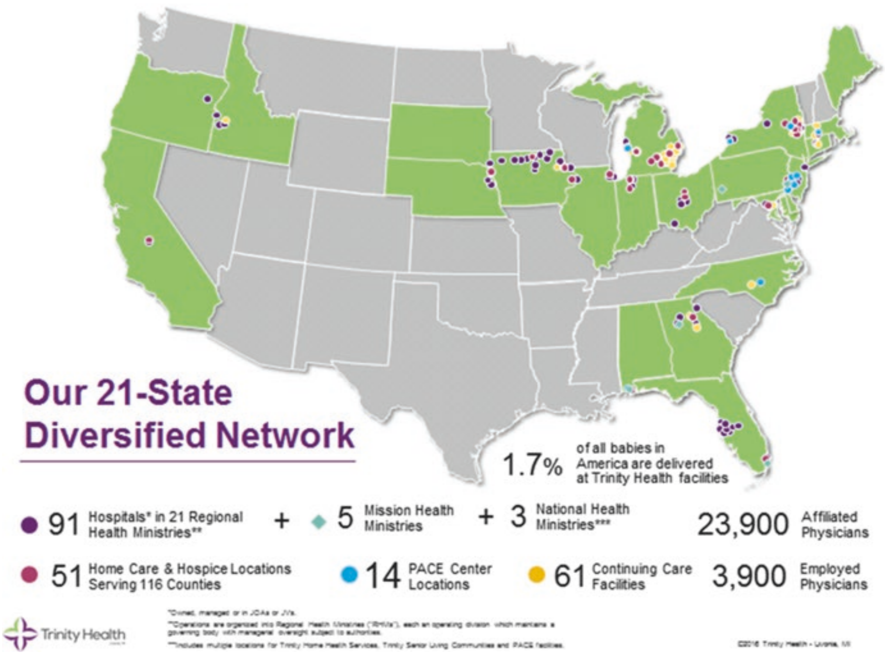


Fig. 7.1.1 Trinity health

Trinity Health's strategic plan, titled "People Centered Care 2020", focuses on three core areas: (1) Episodic care management for individuals with a focus on efficient and effective episode delivery initiatives; (2) Population health management with a focus on efficient care management initiatives; and (3) Community health and well-being with a focus on serving those who are poor, other populations, and impacting the social determinants of health. The Trinity Health strategy is designed to meet the requisites of the Triple Aim: better health, better care, and lower costs.

The integration of the two organizations has led to a complex data environment with multiple source applications in use across the various continuum environments. Although complex, Trinity Health has one of the largest data warehouses within the nation with more than 13 million unique patient records providing a data rich environment for Trinity Health to leverage for big data analytics and nursing research.

Nursing at Trinity Health, over the last 10 years, with the implementation of the electronic health record (EHR), has focused on capturing structured and standardized information electronically across facilities and care venues. This focus now allows for the secondary use of data to study outcomes measurements, practice level improvements, surveillance, population health, clinical research and decision support (Brokel et al. 2012).

7.1.2.1 Trinity Health Data Warehouse: A Cross-Continuum Data Environment

The Trinity Health data environment is comprised of five data flow layers that allow for normalizing, indexing and mastering patient and provider level data for clinical, operational and financial dimensions. The first layer, the source systems layer, represents the core systems across all Trinity Health venues of care. These systems are comprised of both internal systems, housed by Trinity Health, and external systems, hosted by outside organizations in the cloud or subscription based applications. The second layer, the discovery layer, is where the data from the source systems sit into a persistent state. The data is loaded in its natural state into the discovery layer with little to no quality control. The goal of the discovery layer is to load source data quickly so it can be analyzed for business intelligence. The third layer, the integrated data layer, is where data from multiple source systems are integrated into one model. The model conforms to the third normal form (3NF) data model, a model that is used to normalize a database design to reduce the duplication of data and allow for flexible data integration. The fourth layer, the semantic layer, abstracts and simplifies the complexity of the integrated data model, providing multiple business friendly views of data assets depending on needs. The last layer, the analytics layer, is where the business users interact with the data. This last layer represents the big data ecosystem within the vast data environment (see Fig. 7.1.2).

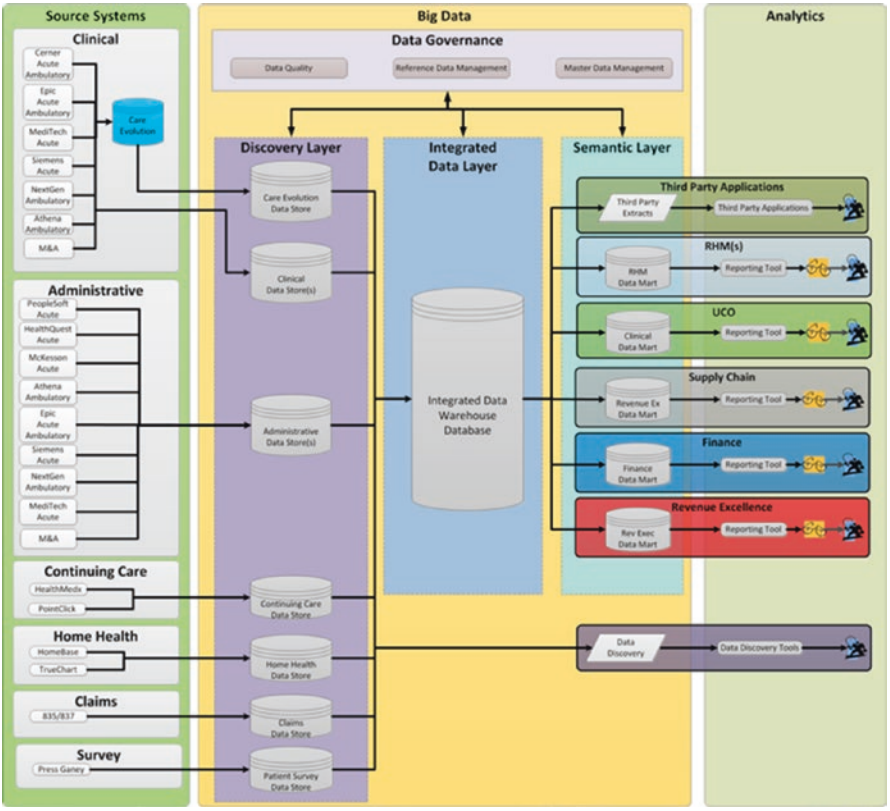


Fig. 7.1.2 Trinity health data warehouse-future state analytic infrastructure (courtesy of Rob Katofiasc and Marian Moran)

7.1.3 Case Studies

Since its big data summit in 2014, Trinity Health has launched or completed several analyses that put big data to work making new discoveries for nursing care. These new discoveries identified correlations between nursing interventions or actions and patient outcomes and in return have informed clinical practice requirements.

7.1.3.1 Interdisciplinary Plans of Care (IPOC) Case Study

Trinity Health developed Interdisciplinary Plans of Care (IPOCs) to guide the delivery and documentation of care, using condition-specific guidance distilled from published evidence for nursing and other professionals including respiratory, spiritual care, rehabilitation care, and clinical nutrition. The goal of IPOC development and usage was to assure consistent care delivery across all Trinity Health hospitals by embedding IPOCs within the clinical workflows and the EHR (Gardiner et al. 2014; HIMSS. HIMSS CNO-CNIO vendor roundtable 2015). IPOCs prompt nurses to make specific observations and document the progress a patient makes towards a condition-specific goal. Trinity Health has 141 IPOCs, with 497 patient care problems for nurses and ancillary providers to select based on the patient's specific condition. In addition to the use of disease specific condition IPOCs, the Adult Core IPOC, consisting of sub-phases for *Deficient Knowledge, Risk of Infection, Difficulty Coping Related to Hospital Stay, Pain, Risk of Deep Vein Thrombosis, Fall Prevention,* and *Risk of Pressure Ulcer* are initiated on all adult patients in medical/surgical and ICU units.

Trinity Health hypothesized that IPOC usage might affect quality outcomes such as mortality. To test this hypothesis, inpatient mortality rates with and without IPOCS were compared using data from the Trinity Health Data Warehouse. Administrative medical records of 165,203 adult medical/surgical discharges for a 12 month period for 18 hospitals across the United States were abstracted. It was noted that IPOC'S guided care in most discharges (see Table 7.1.1). Among the IPOC discharges, the risk of mortality was about half of the mortality in discharges without IPOC guidance. However, the relative risk of mortality remained unchanged when adjusted for acuity factors, despite the confounding influence of higher IPOC usage among higher acuity patients. The study demonstrated that structured documentation, supported by condition specific IPOC's, resulted in lower mortality rates irrespective of acuity. Trinity Health has now incorporated the use of both the Adult Core IPOC and a disease specific IPOC into its nursing practice. It is unclear from the data sets whether the observed decline in mortality rates was causal or associative with IPOC use. Further analysis is needed to understand the causation.

In looking at the use of the Adult Care IPOC's and a disease specific IPOC's, Trinity Health studied data from patients with a primary or secondary diagnosis of congestive heart failure (CHF). The study demonstrated lower mortality risk in patients with disease specific IPOCS, such as Cardiovascular Management or CHF, when compared individually to just the Adult Core IPOC. Hence, the data for congestive heart failure shows that any IPOC is better than no IPOC. Further, condition-specific IPOCs are better than the Adult Core IPOC alone. For primary CHF, the specific CHF IPOC appears slightly better than the general Cardiovascular Management IPOC, but the best performance was obtained when all three (Adult Core, CHF and Cardiovascular Management IPOCs) were used. Patients with a secondary CHF diagnosis, who had the Adult Core with the Cardiovascular Management IPOCs initiated, performed slightly better compared to patient with the Adult Core and CHF IPOC's. Because most of the secondary CHF patients have very acute primary diagnoses, patients fared better with the IPOC specific to their primary condition (see Table 7.1.2).

The case study demonstrates how system-wide, structured documentation supported by IPOC's does improve the quality of care to patients. This also illustrates the value of big data to inform consumers, government agencies, and other health professionals how nursing actions deliver quality care and advance the Triple Aim.

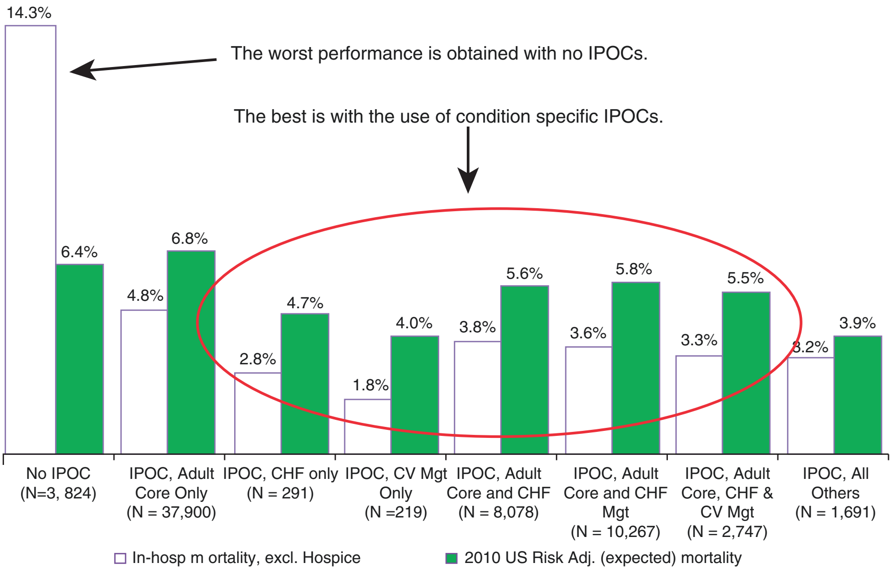
Table 7.1.1 IPOC data-number of inpatient records by health ministry (Trinity legacy) with IPOC information integrated at the patient record level

	2011	2012	2013	2014	2015	Total
Total	52,669	189,745	232,833	267,310	293,510	1,036,092
Holy Cross	27,713	31,226	27,990	31,115	34,612	152,656
Oakland	17,441	18,428	17,216	18,073	20,002	91,160
Dubuque	7515	8148	7049	7868	8580	39,160
Boise		15,299	14,428	14,259	15,733	59,725
Mishawaka		12,903	11,501	13,456	14,746	52,611
Sioux City		10,437	8483	8910	9254	37,088
Livonia		13,906	11,234	14,283	15,637	55,062
Pt. Huron		3553	1535	2752	3274	11,115
Ann Arbor		30,393	27,738	29,915	32,168	120,220
Gr Rapids		16,048	14,446	15,770	18,227	64,492
Mason City		10,771	8670	9027	9410	37,878
Muskegon		8452	6172			14,667
Clinton		4552	3879	4116	4261	16,808
St. Anne’s		2537	12,843	15,879	18,894	50,153
Mt. Carmel West		2277	12,589	13,940	15,396	44,202
New Albany		815	4453	4362	4301	13,931
Fresno			15,776	20,830	21,770	58,376
Mt. Carmel East			13,510	19,185	20,558	53,253
Hackley			6527	7411	9427	23,365
Chelse			3522	3644	3694	10,860
Livingston			3045	2749	2759	8553
Lakeshore			277			277
Nampa				4717	5150	9867
Ontario				2437	2722	5159
Plymouth				1754	1989	3743
Baker City				858	903	1761

7.1.3.2 Pressure Ulcer Case Study

Trinity Health engaged with a local university to analyze gaps in care. The group settled on pressure ulcers as the first condition to study. A review of the literature showed an increase in pressure ulcer risk in African Americans compared with European Americans. Using primarily nursing observation data stored in the Trinity Health data warehouse, the group discovered that the risk of pressure ulcers was equivalent between races. Further, the group discovered that smaller body mass index was a much more important factor than race as previously thought (Pidgeon 2013). The results of the study were used to inform clinical nurses that careful documentation of body mass is important in assessing pressure ulcer risk.

Table 7.1.2 Mortality performance by IPOC usage-patients with primary or secondary diagnosis of CHF



7.1.3.3 Venous Thromboembolus (VTE) Advisory Case Study

As part of the general EHR deployment, Trinity Health has a VTE advisor algorithm embedded within the EHR which is used for all admissions to assess VTE risk and offer prophylactic nursing and pharmacological options. For clinicians, the VTE advisor offers insight and a double-check mechanism for assessing risk and steps to prevent VTEs in their patients. The use of structured nursing documentation such as allergies, laboratory results, weight, documentation in the medication administration record and other information relevant to the VTE risk assessment enables the advisor to give precise prophylaxis recommendations.

As part of ongoing EHR value (return on investment) assessments, Trinity Health analyzed the effectiveness of the VTE advisor as a suggested preventive step. This study demonstrated that prevention of VTE was higher among providers who used the VTE advisor compared to those that did not. Further, it was found that earlier use of the VTE advisor was associated with shorter length of stay, fewer hospital acquired VTE's, lower in-hospital mortality and lower direct variable cost per case. This study demonstrated how observation and documentation by nurses helps drive a highly important preventive prophylaxis regimen. When documentation and observation is guided through the VTE advisor, the precision of the prophylaxis is superior to the prophylaxis alone.

7.1.3.4 General to Specific and Failure to Diagnose Case Study

As part of an ongoing malpractice risk analysis, Trinity Health discovered that failure to diagnose within an emergency department (ED) setting contributed greatly to overall malpractice claims. However, actually observing a failed diagnosis is difficult to capture within an EHR. The use of a proxy allows for a figure to approximate in place. Choosing a proxy for this uncaptured phenomenon, the proxy stated that a patient returning to the ED within 10 days of a prior ED visit for the same clinical condition is at high risk of becoming a failure to diagnose claimant. Using the Center for Medicare/Medicaid Services (CMS) Clinical Classification System (CCS), Trinity Health developed an algorithm to classify each ED admissions chief complaint to a general clinical category. These clinical categorizations ranged from general (abdominal pain) to specific conditions (appendicitis). With the general to specific categorizations, it was discovered that patients who present with general abdominal complaints and leave with a specific diagnosis are half as likely to return within 10 days. Further, when expending no fewer than the median number of diagnostic resources, patients are twice as likely to leave the ED with a specific diagnosis. This finding will lead to new ED discharge advisors or possibly to different follow-up care for those leaving without a specific diagnosis.

This case study demonstrated that the delivery and documentation of diagnostic activities, primarily facilitated by nurses, helped transition general patient complaints to a specific diagnosis. The act of moving from general to specific delivered higher quality patient care and lower malpractice claims.

7.1.4 Conclusion

Modern nursing care requires copious amounts of data from observations and assessments. However, no longer is this data disregarded as valuable for use in secondary data analysis. As shown in the case studies described, liberating nursing data allows for the development of new patient care paradigms. Efforts over the years to transition from free text notes to structured documentation has contributed to new discoveries and guides us toward the Triple Aim of better health, better care at lower costs. Big data science plays a key role in the future of nursing as it offers key clinical insights to inform and transform evidence-based practices that can truly deliver people centered care.

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