Decisions Through Data: Analytics in Healthcare

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EXECUTIVE SUMMARY

The amount of data in healthcare is increasing at an astonishing rate. However, in general, the industry has not deployed the level of data management and analysis necessary to make use of those data. As a result, healthcare executives face the risk of being overwhelmed by a flood of unusable data. In this essay I argue that, in order to extract actionable information, leaders must take advantage of the promise of data analytics.

Small data, predictive modeling expansion, and real-time analytics are three forms of data analytics. On the basis of my analysis for this study, I recommend all three for adoption. Recognizing the uniqueness of each organization’s situation, I also suggest that practices, hospitals, and healthcare systems examine small data and conduct real-time analytics and that large-scale organizations managing populations of patients adopt predictive modeling. I found that all three solutions assist in the collection, management, and analysis of raw data to improve the quality of care and decrease costs.

For more information about the concepts in this essay, contact Ms. Wills at mjwills@crimson.ua.edu. Ms. Wills is the first-place winner of the undergraduate division of the 2014 ACHE Richard J. Stull Student Essay Competition in Healthcare Management. For more information about this competition, contact Sheila T. Brown at (312) 424-9316.
INTRODUCTION
By 2015, the average hospital will produce more than 665 terabytes of data, which is equivalent to 697,303,040 megabytes (Pogorelc, 2013). While the volume of healthcare data is rapidly increasing, healthcare organizations are searching for better data management solutions.

The consulting firm Frost & Sullivan (2012) suggests that “while this data is being hailed as the key to improving health outcomes and reducing healthcare costs, the sheer volume of data is so overwhelming that most organizations are unable to take full advantage of it with their current resources.” Indeed, one recent survey of physicians and hospital executives found that too much healthcare data is available and not enough applicable information accompanies the data (Wolters Kluwer Health, 2011). Westby G. Fisher, MD (2012), a physician with NorthShore University HealthSystem, based in Evanston, Illinois, says, “There’s so much data that we risk getting lost in it.” The increasing amount of healthcare data is a pressing concern that must be addressed because it threatens the efficiency of an organization (Burns, 2013).

BACKGROUND
Fortunately for the healthcare industry, the business sector has already addressed this problem. To not only manage the overwhelming amount of data but also improve operations, businesses turned to data analytics (Kayyali, Knott, & Van Kuiken, 2013). IBM defines data analytics as “the systematic use of data and related business insights developed through applied analytical disciplines (e.g. statistical, contextual, quantitative, predictive, cognitive, other [including emerging] models) to drive fact-based decision making for planning, management, measurement, and learning” (Cortada, Gordon, & Lenihan, 2012). With the need to become increasingly cost efficient, predict health trends, eliminate waste, and implement effective practices, data analytics offers solutions for improving the quality of care, containing costs, and managing operational tasks (Prewitt, 2012).

One example of the use of business analytics is the loyalty cards Target Corporation uses with its customers. The loyalty cards allow the company to track a customer’s purchases and predict future buying trends. Target can send coupons or advertisements to customers depending on their purchasing patterns. Another example in retail is Amazon.com, which uses business analytics to offer personalized purchase recommendations to customers, accounting for 35% of purchases made. Information offered by data analytics allows companies such as Target and Amazon.com to maximize revenue sources and tailor marketing to customers (Datoo, 2013).

While the implementation of data analytics in healthcare is relatively new, it has been met with resistance. The complex nature of the healthcare industry—which includes a provider’s desire for independence, inadequate technological infrastructure, and disconnected systems—has, until recently, limited organizations’ ability to incorporate the level of sophistication in data analytics that has become common.
practice in other sectors (Groves, Kayyali, Knott, & Van Kuiken, 2013).

Further compounding the problem is the traditional mind-set that “all healthcare is local,” meaning that healthcare organizations often have felt little need to invest in information technology (IT). This sense of complacency has been shattered by advances in healthcare IT spurred by a variety of government mandates, such as those called for in the Health Information Technology for Economic and Clinical Health (HITECH) Act and the Affordable Care Act. The outcome is the rapid adoption and utilization of IT in the healthcare industry and the resulting proliferation of unstructured data (Burns, 2013). Thus, the stage is set for the application of data analytics in healthcare (Manyika et al., 2011).

Kaiser Permanente, headquartered in Oakland, California, has shown the way forward through its implementation of HealthConnect, which allows for data exchange and integration of electronic health records (EHRs). HealthConnect has saved Kaiser Permanente approximately $1 billion while improving the disease management of patients with cardiovascular disease (Kayyali et al., 2013), as it allowed the organization to track and work with patients to better control their blood pressure, a key risk factor in cardiovascular disease (Kaiser Permanente, 2013).

Brigham and Women’s Hospital, in Boston, Massachusetts, uses a balanced scorecard that combines clinical, financial, and departmental data as its data analytics tool. Not only has the balanced scorecard helped reduce average patient length of stay but it has also provided predictive information that helps the hospital determine which departments, treatments, or research areas it should invest in next. The information provided by the balanced scorecard helps track performance trends and works toward reducing infection rates by highlighting areas where care can be improved or greater care or attention is needed, and thus improving overall quality (Mace, 2012).

The question remains, how do practices, hospitals, and healthcare organizations handle the overwhelming amount of data continually accumulating? The answer, as suggested by the retail industry examples offered earlier, lies in data analytics. Data analytics must become common practice in all these types of organizations in order to make sense of the growing amount of healthcare data (Burns, 2013). Small data analytics, predictive modeling expansion, and real-time analytics are three options in the emerging field of data analytics. Each offers a unique approach to managing and analyzing data that would greatly benefit health organizations and practices currently facing burdensome amounts of data.

**Solutions**

**Small Data**

Healthcare leaders are generally aware of big data—the analysis of large amounts of information to highlight health trends, patterns, and possibilities for entire populations or groups of people—but for healthcare managers and organizations, small data may be much more appropriate for translating data to actionable information. In
contrast to big data, small data is the collection of information for a small patient population. Small data offers several ways for a practice, an organization, or a provider to analyze and better understand patient populations. EHRs serve as a tool for collecting and storing patient information, which can be converted to clinical summaries or continuity-of-care documents and then used in small data analytics. For example, small data can be used to highlight the gaps in preventive measures for target and critical patients. Data-driven feedback on possible complications or projected health issues helps emphasize preventive care. As a result, providers may act in a more cost-efficient way to prevent large expenditures that accompany uncontrolled or preventable illnesses (Terry, 2012).

Additionally, small data reports benchmarks or goals for specific patients with chronic conditions. With detailed information on patients, providers are able to monitor and control the conditions. The information shows whether or not treatments are yielding satisfactory results for the patient. When outcomes are unsatisfactory, care managers can then be assigned to better address the condition. By monitoring conditions, providers and healthcare organizations are able to reduce costs in the long run (Terry, 2012).

Small data is an extremely effective tool for primary care management. Unlike big data, small data does not add undue financial strain on a practice or healthcare provider. Instead, it uses the information already collected by EHRs.

Patient-centered medical homes and many small to midsize physician groups are working toward the integration and use of small data. With the detailed information gathered to fulfill Stage 1 meaningful use requirements and through the transition to Stage 2, physicians can extract information about their high-risk patients. By mining small data, they can manage chronic conditions, assign case management, and prevent future complications. Understanding high-risk patients’ complex conditions allows for greater quality and cost containment (Kibbe & Kuraitis, 2012).

Small data analytics does not require substantial monetary investments, but certain costs are associated with integrating a small-scale registry, data warehouse, or data repository that mines data from EHRs in addition to the cost of training personnel and changing existing workflows to use small data. Healthcare organizations can choose the data-mining interface most appropriate for their patient populations (Kolakowski, 2012). As with any other change, especially the adoption of new technology, physicians and staff can be resistant. However, this resistance can be overcome if providers are shown the value to patient care quality (Kibbe & Kuraitis, 2012).

Predictive Modeling
Predictive modeling is another data analytics technique focused on forecasting future medical costs. The model uses patients’ medical information to evaluate health risks and predict their future medical utilization (Ingenix, 2006). A wide variety of predictive modeling algorithms are available, all of which assign a specific risk level or score to
patients (Asparouhov, 2012). Risk scores are determined by risk markers and are assigned to each patient in a particular population (Ingenix, 2006).

By using past diagnoses, demographic details, and other information gathered from EHRs, predictive models forecast individual patient costs, which can then be used by providers and insurers. Consequently, specific patients needing specialized management come to light (Loginov, Marlow, & Potruch, 2012). Some predictive models identify the 1% of a particular pool that drives the majority of healthcare costs. These high-risk, high-cost patients require extensive time, energy, and resources, increasing the overall costs to the provider or organization (Asparouhov, 2012).

Blue Cross and Blue Shield of North Carolina (BCBSNC) uses predictive modeling to understand the needs of its customers. With data that have already been collected, BCBSNC studies current healthcare needs and predicts future health issues by using predictive modeling, thereby working to prevent future health complications and improving customers’ overall health. With 50% of BCBSNC’s costs being driven by only 4% of its customers, predictive modeling allows BCBSNC to expect future health trends and implement initiatives to improve health conditions proactively, which reduces costs (Mace, 2012).

Parkland Health and Hospital System, in Dallas, Texas, launched a predictive modeling system created in-house by a staff physician in 2009. The electronic system scans patients’ information, identifies high-risk patients, and predicts outcomes for those patients. As a result of the predictive modeling system, Parkland Hospital has saved more than $500,000 since the system’s implementation. With a 31% reduction rate in 30-day readmissions for Medicare patients suffering from heart failure, readmission penalty rates are 10 times lower than the national hospital average. The specialized predictive modeling system has also improved Parkland Hospital’s ability to monitor patients and to work toward preventing future complications (Jacob, 2012).

If not used appropriately, predictive modeling can have negative consequences. For example, strictly following predictive modeling guidelines may result in decreased attention to patients as unique individuals. Inefficiently implementing a predictive modeling system can result in wasted resources. Most of the drawbacks to predictive modeling can be prevented if the system is accurately applied (Ingenix, 2006). Many different types of predictive modeling algorithms are available for purchase.

Real-Time Analytics
Unlike batch analytics tools, such as small data and predictive modeling, real-time analytics uses immediate information at the point of care. Instead of making decisions in hindsight through the batch method, real-time analytics allows choices to be made at the bedside. Enabling point-of-care decision making holds the potential to truly revolutionize methods of patient diagnosis and treatment (Ozga, 2013). Real-time analytics systems generate updated information concerning a patient’s history and current status and
offer suggestions for diagnosis and treatment (Murphy, 2013).

Real-time analytics goes beyond the mere collection of patient data. Although currently a great deal of point-of-care patient data can be obtained from equipment, that information is typically recorded but underutilized. Real-time analytics focuses on the recording of point readings and streaming data, but more important, it analyzes the data at the point of care to present immediate and actionable information for providers. For example, the analysis can show possible drug interactions, suggest treatment methods, and provide alerts for future complications or developments (Taylor, 2010).

Real-time monitoring of patients continually adds information to the ever-increasing supply of data (Taylor, 2010). Tom Olenzak, director of innovation at Independence Blue Cross in Philadelphia, has high hopes for the expansion of real-time analytics. He believes treatment will become more accurate and efficient once physicians can receive real-time information, such as blood glucose levels, about a patient at the point of care.

In another example of integrating real-time analytics, the University of Texas Southwestern Medical Center in Dallas is analyzing data from EHRs. The system, whose deployment is currently limited to readmission rates, helps clinical staff keep track of risks and complications so they can focus in particular on patients with a high risk of readmission within 30 days of discharge. As a result, readmission rates have decreased by 5%, which signals an increase in the quality of care as well as a decrease in cost (Bresnick, 2013b).

Real-time analytics is the most cutting-edge option of the three discussed here, but it is also the most costly to deploy and requires the most training. It requires complete integration of all data, including registries, silos, hardware systems, and software, as well as internal technical support and technical maintenance. But while the input (financial and technical investment) is great, the output holds even greater possibility for reducing cost and increasing quality (Torres, 2009).

Recognizing the promise of real-time analytics, Hunterdon Healthcare System has created a hospital performance management system that includes real-time data. Pressure on executives to support up-to-date data came not only from physicians but also from managers, administrators, and financial advisers. Hunterdon executives realized that the overwhelming amount of mismanaged data was draining their resources and energy (Mamary, 2012).

Consequently, they chose to channel the data through a system of real-time analytics that will ultimately transform treatment methods, as it highlights information that may be missed during retrospective review. As a result, Hunterdon has experienced improved outcomes.

**Recommendations**

After exploring three approaches to data analytics—small data, predictive modeling, and real-time analytics—I recommend that healthcare organizations examine all three solutions to determine which suits their particular needs. Each
offers a different way to manage the overwhelming amount of healthcare data and provide actionable information. By examining their current technological infrastructure and determining the investment they are willing to make, organizations can gauge what type of data analytics system will perform best for them (Prewitt, 2012).

Predictive modeling works best for large insurance companies and third-party payers. Third-party payers have long performed data analysis as a routine part of their business and continually seek new, advanced methods of data analytics. It is a good fit for insurers because the actionable data it derives allow them to assess risk pools, predict future trends, and determine reimbursement rates with some accuracy (Mace, 2012).

For practices, hospitals, and healthcare organizations, small data and real-time analytics hold the most promise. Small data uses micro-level data, which are already collected by EHRs. Small-data systems provide actionable information for a practice or an organization (Gooch, 2013) because they are easy to integrate into technical systems and offer management and predictive information in dashboard form that is digestible for small to midsize healthcare organizations. The actionable information is then used to drive improvements in the quality of care and decreases in costs (Kibbe & Kuraitis, 2012).

This improvement cycle is demonstrated by a partnership between Community Care of North Carolina (CCNC), a private–public medical home, and GlaxoSmithKline, a pharmaceutical company. The collaboration resulted in a small data analytics model that takes small amounts of data, such as patient-specific medical details; analyzes the data; and predicts outcomes. Instead of simply notifying CCNC that a problem exists, the model explains what the problem is and offers suggestions on how to fix the issue. This partnership-based small data model is delivering high-quality outcomes, with one CCNC executive noting that it has had a significant impact on the organization’s overall efficiency and coordination (Gooch, 2013).

Real-time analytics also offers great possibilities for hospitals, practices, and healthcare organizations. Especially in inpatient settings, the status of a patient can change instantly. Real-time analytics provides physicians with continually updated information that allows for more effective and timely care management and proactive treatment methods. Eliminating the delay for analysis of data, real-time analytics reduces treatment time in inpatient and outpatient settings, offers potential outcomes for consideration, and reduces costs (Bresnick, 2013a).

**Conclusion**

Healthcare data will continue to accumulate rapidly. If practices, hospitals, and healthcare systems do not actively respond to the flood of unstructured data, they risk forgoing the opportunity to use these data in managing their operations (Burns, 2013). Small data and real-time analytics are two methods of data analytics that allow practices, hospitals, and healthcare organizations to extract meaningful information.
Predictive modeling is best suited for organizations managing large patient populations. With all three methods, the applicable information mined from raw data supports improvements in the quality of care and cost efficiency (Prewitt, 2012). Currently, opportunities for improvement often arise only in the wake of a problematic situation. The use of small data, real-time analytics, and predictive modeling will revolutionize the healthcare field by increasing those opportunities beyond reacting to emerging problems.

REFERENCES