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Why predictive modeling in healthcare requires a data warehouse

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> The evidence that predictive modeling (also known as "health forecasting") can improve patient outcomes remains thin.

INTRODUCTION

The healthcare industry has begun to adopt predictive analytics for a variety of purposes. Viewed by experts as a prerequisite for population health management, these statistical tools are being used to forecast which patients are likely to be readmitted to the hospital. Some healthcare organizations also apply predictive analytics to large clinical and administrative data sets in an effort to identify and intervene with certain patients before they become seriously ill.

At times, predictive analytics can be valuable. For example, a predictive modeling application that predicts the chances of patients developing a serious chronic condition or having a heart attack was successfully tested in a Kaiser Permanente clinic. As a result of clinical interventions, the risk of patients at that site developing coronary artery disease dropped 22 percent on average, compared to a decline of 9 percent in a clinic that didn't use the tool.[1]

An Israeli study showed that using a five-point scoring tool could predict hospital readmissions with 80 percent accuracy.[2] Other studies have used different models to identify patients who were at an elevated risk of being readmitted.[3-4]

Despite these successes, however, the evidence that predictive modeling (also known as "health forecasting") can improve patient outcomes remains thin. In their article on risk stratification and predictive modeling, "The Promise and Peril of Healthcare Forecasting," authors Frank Wharam and Jonathan P. Weiner note:

> Health insurance companies, similarly, use actuarial risk models to compute the chances that particular individuals will cost the insurers more than they pay in premiums.

> There is little evidence regarding how or whether [health] forecasting improves healthcare value. This is due to both the modest level of research and what is termed the "impactibility" problem. That is, even if prediction algorithms accurately identify at-risk patients, intervening to achieve desired outcomes is often inhibited by limitations of current disease management approaches or the general state of medical science.[5]

This is a key point in any discussion of predictive analytics. Unless the results of health forecasting can be translated into effective interventions with individual patients, the analytic tools will be useless. So healthcare organizations must develop the infrastructure and the culture required to turn the data into action. That infrastructure must provide the ability to generate timely reports and use automation tools to apply intervention strategies across a patient population.

BACKGROUND

Using computers to predict risks is not new. The Defense Department has long employed predictive analytics to model nuclear war scenarios or optimize the order of battle. The life insurance and casino gaming industries have also invested heavily in programs that help them calculate their odds of success.

Health insurance companies, similarly, use actuarial risk models to compute the chances that particular individuals will cost the insurers more than they pay in premiums. Until the Affordable Care Act took effect, health insurers utilized this type of analysis to determine whom to exclude from coverage and how much to charge the people they did cover. Some health plans have also been using it to intervene with high-risk patients in disease management programs.[6]

With the emergence of accountable care organizations (ACOs) and value-based reimbursement, many hospitals and healthcare systems have also begun to recognize that they need predictive analytics and health risk stratification to manage population health and deliver care more cost effectively. At the same time, provider organizations are now focused on reducing readmission rates so they won't be financially penalized by Medicare.

The current interest in predictive modeling is part of a larger trend to employ business and clinical intelligence (B&CI) applications in healthcare. Until recently, organizations that had the ability to mine and analyze data were mostly conducting retrospective analyses.[7-8] Today, as their analytic capabilities mature, a growing number of healthcare systems are adopting predictive tools. Most organizations, however, are either in the early stages of building data warehouses or are using standalone analytics for particular purposes without the infrastructure required to apply these tools on a broader scale.[9]

CHALLENGES FOR PREDICTIVE ANALYTICS

Predictive algorithms enable computers to recognize patterns in data and draw deductions from those patterns that show the likelihood of particular events occurring in the future. This kind of algorithm is used in many types of activities, ranging from detection of credit card fraud and the optimization of search engines to stock market analysis and speech recognition.

To create a predictive algorithm, developers first define a problem, gather data, and run and evaluate different models to solve the problem. Next, they select the best model and validate it. Finally, they test the model by running it against a real-world dataset.

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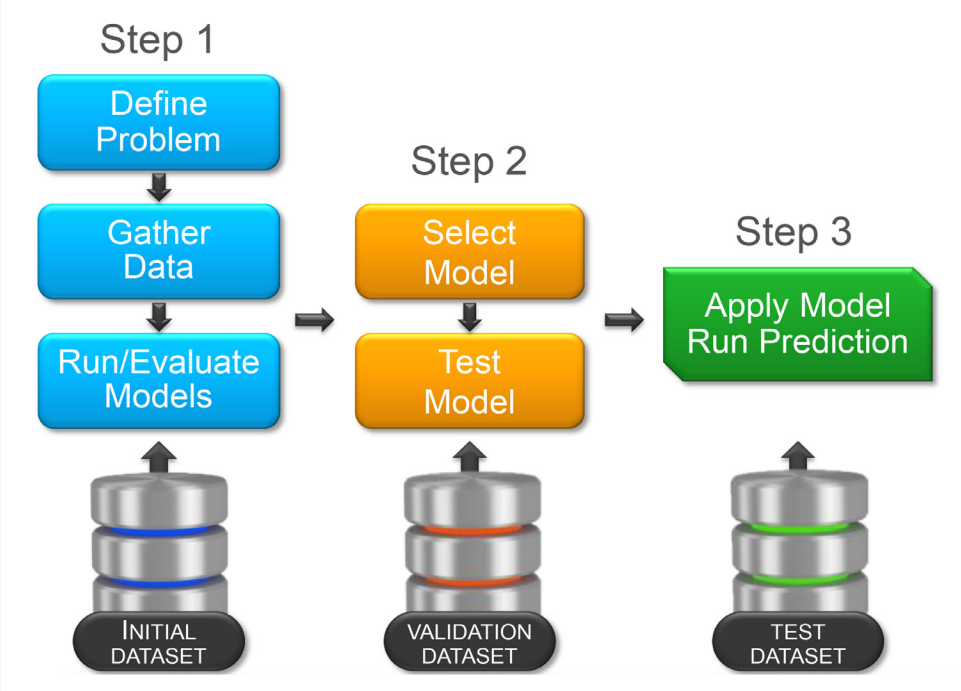

Figure 1: The Modeling Process

To improve the accuracy of predictive modeling, developers may take an approach known as "supervised learning," in which the outcome is known ahead of time and is used to "train" an algorithm. But in healthcare, many important kinds of patient outcomes are not captured as structured data. Without outcomes data to train the algorithm, it's difficult to apply a supervised learning model.

Some outcomes of interest can readily be measured. For example, if a predictor is designed to identify the patients who are at the highest risk of being readmitted, the outcome is a readmission within a certain period of time. Similarly, if an algorithm predicts which patients are most likely to have out-of-control hypertension or to be noncompliant with particular medications, those endpoints may be documented in structured data that can be analyzed.

In contrast, the health status of patients after discharge may not be available unless patients fill out functional status surveys at specified intervals. Also, the follow-up on most patients after discharge or between office visits is limited or nonexistent. As a result, only the data generated in the EHR during a visit or an episode of care may be available. Diagnoses, lab values, medications, and vital signs from these encounters appear in a data warehouse, but they don't reflect the time period between visits, which would show how the patient fared between visits or episodes.

Even the episodic data are frequently not structured in the EHR, partly because some providers don't enter them in the ubiquitous pull-down check boxes. For example, studies have shown that patient diagnoses are often missing from discrete data, although they usually appear somewhere else in the record.[10]

Paid claims data, in contrast, always include diagnostic and treatment codes. Moreover, claims data show the services and prescriptions that patients received from providers outside an organization or network. But claims have a built-in lag time, so they're not very good for predicting what might happen in the near future.

> A generic readmission predictor developed in-house, for example, was validated to perform with a 79 percent positive predictive value (PPV). In contrast, a readmission predictor developed by Health Catalyst and applied to patients with congestive heart failure has a 91 percent PPV.

Furthermore, claims are not precise enough to describe in detail what has been done for the patient in various care settings.

For most analytic purposes, organizations rely on a combination of clinical and claims data, if they have access to the latter. ACOs, in particular, are expected to depend on claims data for years to come.[11] But to make the best use of predictive analytics, healthcare organizations must build data warehouses capable of aggregating, normalizing and cleaning up this data and presenting it in a format that is easy to use in report generation.

SPECIFICITY AND CLINICAL INSIGHT

Predictive modeling is more accurate when it is applied to specific subpopulations and care settings than when it is used generically across cohorts and organizations. A generic readmission predictor developed in-house, for example, was validated to perform with a 79 percent positive predictive value (PPV). In contrast, a readmission predictor developed by Health Catalyst and applied to patients with congestive heart failure has a 91 percent PPV. The latter model is more accurate because the variables it uses are more specific to the population involved. In other words, the very features that characterize a specific condition well are the same attributes that can train an accurate predictor. Additional information is available at http://pages.healthcatalyst.com/rs/healthcatalyst/images/9.24.2013.DavidCrockettPredictiveAnalyticsWebinar.pdf.

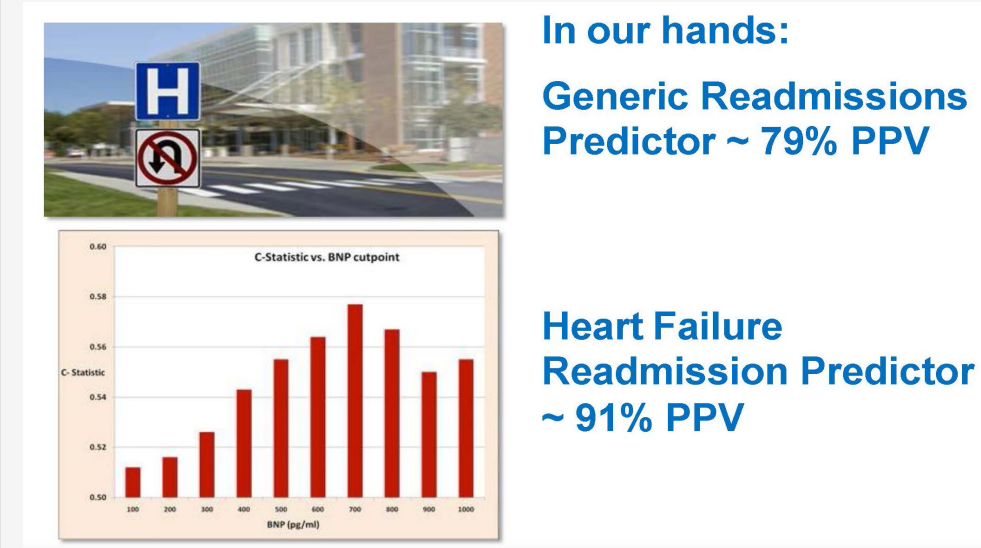

Figure 2: Specific Improves Accuracy

A study by researchers at Emory University makes the same point in a different way. The researchers used an algorithm to predict readmission of post-surgical patients to a children's hospital based on three variables: how many days a patient had been in the hospital, whether or not the patient had failed to thrive during the pre-operative period, and whether or not the patient was Hispanic. Researchers found that these indicators predicted most readmissions to that hospital.[12] However, this algorithm could only be applied to areas where there are a lot of Spanish speakers, who are less likely to understand discharge instructions spoken or written in English.

TURNING INSIGHTS INTO ACTION

- Link predictions to specific clinical priorities, such as raising the percentage of hypertensive patients with blood pressure controlled.
- Set up new workflows and use automation solutions to take advantage of predictive analytic insights.
- Apply analytics to slowly changing clinical situations, not emergencies.
- Use analytic tools with longitudinal rather than episodic data.
- To improve predictive accuracy, use patient data obtained through surveys and remote monitoring.
- Build an advanced data warehouse to integrate all available information on a patient in near real time.

Ironically, even without fancy predictive analytics in use, any physician or nurse would recognize this language barrier difficulty. Similarly, they know that low patient literacy, poor understanding of discharge instructions, failure or inability to make an appointment with a primary care doctor, and lack of communication between inpatient and ambulatory providers are all factors in readmissions.[13-14] What is needed to solve these problems is not analytics, but action grounded in clinical experience.

Even where predictive analytics can help improve the quality of care, clinical insight is critically important to support and inform the use of these tools. Unfortunately that insight isn't always available. For example, Northwestern University found that 30 percent of their own patients under chronic condition management were unable to participate in treatment protocols. The reasons were related to cognitive, economic, physical or geographic inabilities, religious beliefs, contraindications to the protocol, and/or voluntary non-compliance. These atypical patients must be treated or reached in a unique way, and predictive algorithms, data collection strategies, and interventions must be adjusted for their attributes. More information is available at http://www.healthcatalyst.com/webinar/predictive-analytics-its-the-intervention-that-matters/.

Clinical observations can also improve the accuracy of predictors. To illustrate, a patient wellness metric known as the Rothman index requires users to input not only structured data such as lab values and blood pressure readings but also the nursing assessment of the patient.[15] The predictor would be a failure without the nursing notes, because it would be an incomplete snapshot of the patient. But the combination of the nursing assessment with the lab values and the vitals makes the Rothman index fairly accurate.

Predictive analytics, as noted earlier, is not very useful unless it can be applied to patient care to improve outcomes and efficiency. These tools, which might better be described as "prescriptive" analytics, should link predictions to specific clinical priorities, such as increasing the percentage of hypertensive patients who have their blood pressure controlled. The predictors should also be focused on measureable events, such as cost effectiveness, clinical protocols or patient outcomes.
To use these tools successfully, healthcare organizations must be willing to change their culture and their work processes. New workflows should be set up and organizations should deploy automation solutions to take advantage of the insights afforded by predictive modeling. Organizations must persuade clinicians to trust analytics that have been proved valid for particular kinds of clinical decisions.

Because of the potentially serious consequences of making the wrong decision in an emergency, predictive analytics are sometimes easier to apply to slowly changing situations such as chronic disease management, elective procedures, weaning patients off ventilators, and antibiotic protocols.

For optimal use in chronic disease management, predictive analytics should be applied to longitudinal rather than episodic data. This requires getting patients involved. For example, patients might be asked to fill out online functional status surveys at regular intervals. In select healthcare settings, remote monitoring data may also be routinely available. By feeding this kind of data into the predictive model for the target patient population over time, and analyzing it by age, gender, medication, geographical location, and other variables, researchers can develop much more specific predictive models than they could with a general hospital or ambulatory care population.

> By accurately predicting who is most likely to get sick, organizations can set priorities and focus their care management and patient engagement activities on the people who need it the most.

It is impossible to aggregate and normalize this information for analysis without an advanced data warehouse that allows continuous updating and flexible report generation. To deliver actionable insights, moreover, this data warehouse must be able to integrate all of the available information on a patient in the context of what clinicians want to know. In a rich EDW environment where patient details are available in this context and can be fed into a predictive tool, the interventions driven by that predictor are more likely to be successful than they would be when a single-purpose, point solution is applied to data in an information silo.

Population health management

One of the fastest ways to derive value from predictive modeling is to apply it to population health management. This involves a form of predictive analytics known as risk stratification, which classifies patients by their risk of getting sick or sicker within the next year or some other time period.

In population health management, the ability to do this is critical, because only 30 percent of patients who are high-risk today were in that category a year ago.[16] By accurately predicting who is most likely to get sick, organizations can set priorities and focus their care management and patient engagement activities on the people who need it the most.

In a 2013 *Issue Brief* published by the Colorado Beacon Consortium, Asaf Bitton, M.D., MPH, FACP, noted, "Risk stratification is an intentional, planned and proactive process carried out at the practice level to effectively target clinic services to patients." In that same *Brief*, the Consortium's Executive Director, Patrick Gordon, identified three goals for risk stratification:

- Predict risks
- Prioritize interventions
- Prevent negative outcomes (e.g., disability and death, as well as unnecessary costs)[17]

Risk stratification requires sophisticated algorithms, robust registries or data warehouses, and the ability to integrate multiple sources of data. "The more data you have, the better able you are to predict outcomes," Gordon noted. "Access to more actionable data within a process driven by clinical judgment and shared decision-making improves the ability of a practice team to proactively align resources with patient needs."[18]

Administrative Applications

An organization can also use predictive analytics to increase the efficiency of certain operations. For example, if there are certain disease patterns – such as biannual outbreaks of upper respiratory infections in children or a spike in asthma attacks triggered by worse air quality in certain seasons – algorithms can be devised to help healthcare systems better manage their supply chain and staffing.[19] If an organization can predict changes in demand for services, it can ensure that sufficient supplies are on hand or that nurse staffing is adequate take care of patients on a particular shift.

COMPARISON OF CURRENT SOLUTIONS

Solution	Pros	Cons
Outsource analytics to service firms	No upfront investment. Can help improve reporting. Can benchmark performance.	Limited types of analyses. Inability to adapt tools to meet organizational needs
Best-of-breed solutions	Detailed analytics for specific domains—e.g., readmissions.	No overall view of patient care and costs. Can't be integrated into broad IT infrastructure. Subpopulations can't be analyzed.
EHR-based solutions	Can be used to generate reports for Meaningful Use	Analytics not robust or flexible. Views limited to EHR data.
Advanced data warehouse solution	Highest degree of flexibility. Can adapt to changes in healthcare environment. Allows meaningful clinical interventions.	Longer lead time to build optimal infrastructure.

Healthcare organizations can approach the use of analytics solutions, including predictive analytics, in several different ways. One option is to outsource their business and clinical intelligence work to analytics service providers. This approach, which doesn't require any investment in hardware, software, or internal expertise, can help providers improve their internal and external reporting and can enable them to benchmark their performance. But the providers who outsource these functions are limited in the kind of analyses they can perform and are unable to adapt the analytic tools to meet their specific needs.

Second, organizations can adopt "best of breed" point solutions. These standalone applications provide detailed analytics for a specific domain, such as readmissions, but don't supply an overall perspective on patient care and costs. They also can't be easily integrated into a broader infrastructure that would increase their usefulness.

> An approach based on the use of an advanced enterprise data warehouse (EDW) provides the highest degree of analytics flexibility and adaptability.

A standalone predictive tool cannot be used to analyze the health risks of subpopulations because the data is not readily available. For example, unless an organization leverages a data warehouse for predictive analytics, it can't produce comprehensive reports on all patients over 65, all women who recently gave birth, or all people who went to the ER because they recently overdosed on drugs. The warehouse environment allows pertinent but disparate data sources to be mapped and combined. This is the kind of complete information that a predictor needs to distinguish the signal from the "noise" in the data and make accurate forecasts.

Some healthcare organizations look to their electronic health record (EHR) vendors for analytics capabilities. According to a recent survey, more than half of the hospitals that use clinical and business intelligence employ the analytic modules embedded in their EHR or hospital information system. Such tools can be used to generate reports related to Meaningful Use objectives.[20] But these analytics often lack robustness and flexibility. In addition, the data they use comes solely from the EHR. As a result, the analytics lack an integrated view of clinical, financial, administrative, and patient satisfaction data.

Finally, organizations could build an optimal infrastructure for generating analytic insights before deploying predictive analytics. Such an approach, based on the use of an advanced enterprise data warehouse (EDW), provides the highest degree of analytics flexibility and adaptability. It can drive an analytics strategy that will enable an organization to adapt to both short-term and long-term changes in healthcare. Most importantly, this rich EDW environment enables meaningful intervention if the organization connects its analytics to care management. More information is available at http://www.healthcatalyst.com/choosing-the-best-healthcare-analytics-solutions-html.

ANALYTICS ADOPTION MODEL

Organizations that take the road to predictive analytics described above should study the Analytics Adoption Model that was developed by a group of healthcare industry veterans, including hospital CIOs and healthcare consultants. This eight-level model provides a road map for organizations to measure their own progress toward analytic adoption.

Level one of this schema consists of fragmented point solutions that are not integrated with a data repository or with each other. In Level 2, organizations build an enterprise data warehouse (EDW) for clinical and administrative data with a master vocabulary, a patient registry, and basic data governance.

In Levels 3 and 4, providers begin to use the warehouse for automated internal and external reporting. Key performance indicators are visible to both frontline managers and executives. Analytics are used to produce reports required for regulatory and accreditation purposes, specialty society databases, and payer incentives (e.g., the Meaningful Use EHR incentive program, the Physician Quality Reporting System, and the Medicare value-based purchasing program).

The goal of analytics in Level 5 is to measure clinical effectiveness that maximizes quality and minimizes waste and variability. Data governance supports care management teams involved in population health management. The EDW is expanded to include clinical data from labs and pharmacies, as well as claims data.

Level 6 is designed for organizations that take bundled payments and accountable care organizations that share financial risk and reward. Analytics are available at

the point of care to help organizations achieve the Triple Aim of improving quality, efficiency, and the patient experience.

In Level 7, analytics are further expanded to address fixed-fee reimbursement models (i.e., risk contracts). Predictive modeling and risk stratification are deployed to support population health management. Data sources include home-monitoring, long-term-care, and patient-reported outcomes data.

Level 8 expands the role of analytics to include wellness management, physical and behavioral functional health, and mass customization of care. Prescriptive analytics – a combination of insights from predictive analytics with clinical decision support – are available at the point of care to help clinicians determine which interventions are appropriate for each patient. In the future, the data content at this level will include continuous biometric data, genomic data, and familial data.

HEALTHCARE ANALYTICS ADOPTION MODEL

Data binding grows in complexity with each Level

Level 8	Personalized Medicine & Prescriptive Analytics	Tailoring patient care based on population outcomes and genetic data. Fee-for-quality rewards health maintenance.
Level 7	Clinical Risk Intervention & Predictive Analytics	Organizational processes for intervention are supported with predictive risk models. Fee-for-quality includes fixed per capita payment.
Level 6	Population Health Management & Suggestive Analytics	Tailoring patient care based upon population metrics. Fee-for-quality includes bundled per case payment.
Level 5	Waste & Care Variability Reduction	Reducing variability in care processes. Focusing on internal optimization and waste reduction.
Level 4	Automated External Reporting	Efficient, consistent production of reports & adaptability to changing requirements.
Level 3	Automated Internal Reporting	Efficient, consistent production of reports & widespread availability in the organization.
Level 2	Standardized Vocabulary & Patient Registries	Relating and organizing the core data content.
Level 1	Enterprises Data Warehouse	Collecting and integrating the core data content.
Level 0	Fragmented Point Solutions	Inefficient, inconsistent versions of the truth. Cumbersome internal and external reporting.

Note that predictive analytics don't emerge in this model until Level 7 (although they could arguably be used in Level 6, as well). Organizations that attempt to leapfrog the earlier levels in order to apply predictive tools will find their efforts hampered by an inadequate infrastructure. It is impossible to do predictive modeling, for example, before an organization even automates the reporting process in its EDW.

ENTERPRISE DATA WAREHOUSING

To use predictive analytics effectively for improving patient outcomes and managing population health, an organization must have an EDW. Yet by 2011, only approximately 30 percent of U.S. hospitals and healthcare systems had an EDW; a 2013 report suggests that number hasn't changed much.[21-22] Moreover, the vast

majority of those EDWs use an antiquated architecture that isn't flexible enough to make the insights of predictive analytics actionable.

To understand why, one must know the difference between "early-binding" and "Late-Binding™" models for data warehouses.

Data can be "bound" to business rules that are implemented as algorithms, calculations, and inferences acting upon that data. In healthcare, this data binding may be done for calculating the length of stay, attributing a primary care provider to a particular patient with a chronic disease, or data definitions of disease states for patient registries, among other things. In addition, data can be bound to vocabulary terms such as patient identifier, provider identifier, location of service, gender, diagnosis code, and procedure code.

Early-binding models, which characterize most legacy EDWs, are based on large software programs that bind data to business rules or vocabularies before they are compiled. By definition, these are static models. If the software must be modified because of new business rules or requirements, it is a very time- and labor-intensive process that can take 12 to 18 months to complete in a large organization. By the time the changes have been made for a specific kind of predictive modeling, the use cases may have changed, requiring a whole new set of modifications in the program.

In a Late-Binding™ model, programs are broken down into modules or objects that support particular business services and processes. These modules are assembled as needed at run time, rather than being compiled beforehand. By using this kind of architecture, an EDW can provide analytic value in days or weeks rather than months or years. Such an approach allows organizations to adapt easily to changing requirements. More information is available at http://www.healthcatalyst.com/choosing-the-best-healthcare-analytics-solutions-html.

The following fundamental principles apply for all data modeling, especially when used in predictive analytics:

- The key to success in data warehouses is relating data, not modeling data. Data should be modeled only to the extent necessary.
- Data from various source systems should be leveraged directly to minimize the amount of data normalization required.
- Data models should be applied to mapped subsets of data, such as EHR, claims, prescription, cost, and patient satisfaction data.
- Some core data elements are fundamental to nearly all analytic use cases in healthcare. Those elements can be bound early, but remaining data should be bound to other terms and business rules later and only when required by use cases.

CONCLUSION

Predictive analytics are rapidly emerging as a "must-have" class of analytics tools that healthcare organizations can use to manage population health, reduce readmissions, and improve patient outcomes. But providers should not have unrealistic expectations of what these analytics can do. The type and quality of available data, including outcomes data, limit the usefulness of predictive analytics. In addition, organizations must couple these analytics with other tools, such as outreach and care management applications, to access the full potential of predictors in patient care.

Before deploying predictive modeling tools, healthcare systems should develop sophisticated data warehouses. Studies over the past few years show that most organizations still have work to be done in this area, although the path to achieving high-functioning data warehouses is clear. While point solutions and outsourcing options are available, and some EHR vendors offer analytics packages as well, building an EDW that allows the rapid assembly of patient data in context offers the most flexibility and the greatest range of possibilities for using predictive analytics.

The type of data warehouse that an organization chooses is critically important to its eventual success in using predictive analytics. A late-binding EDW enables the healthcare system to move nimbly from one use case to another, providing the timely insights that clinicians can translate into effective action. In contrast, early-binding models are static monoliths that are time consuming and difficult to modify as the requirements of clinicians, administrators, and regulators change.

At the end of the day, the organization that makes the effort to build an advanced, late-binding enterprise data warehouse will be able to successfully implement predictive analytics for a wide variety of purposes. More importantly, the organization will also be able to gauge the effectiveness of resulting interventions. These organizations will be well prepared to meet the manifold challenges facing them as healthcare is transforming.

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About Health Catalyst

Based in Salt Lake City, Health Catalyst delivers a proven, Late-Binding™ Data Warehouse platform and analytic applications that actually work in today's transforming healthcare environment. Health Catalyst data warehouse platforms aggregate and harness large amounts of data utilized in population health and ACO projects supporting over 30 million unique patients. Health Catalyst platform clients operate over 135 hospitals and 1,700 clinics that account for over $130 billion in care delivered annually. Health Catalyst maintains a current KLAS customer satisfaction score of 90/100, received the highest vendor rating in Chilmark's 2013 Clinical Analytics Market Trends Report, and was selected as a 2013 Gartner Cool Vendor. Health Catalyst was also recognized in 2013 as one of the best places to work by both Modern Healthcare magazine and Utah Business magazine.

Health Catalyst's platform and applications are being utilized at leading health systems including Allina Health, Children's Hospital of Wisconsin, Crystal Run Healthcare, Indiana University Health, Kaiser Permanente, Memorial Hospital at Gulfport, MultiCare Health System, North Memorial Health Care, Partners HealthCare, Providence Health & Services, Stanford Hospital & Clinics, and Texas Children's Hospital. Health Catalyst investors include CHV Capital (an Indiana University Health Company), Kaiser Permanente Ventures, Norwest Venture Partners, Partners HealthCare, Sequoia Capital, and Sorenson Capital. Visit healthcatalyst.com, and follow us on Twitter, LinkedIn, Google+ and Facebook.

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