



Predictive Analytics

An Overview for Community Health Centers

2016



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About Capital Link:

Capital Link is a non-profit organization that has worked with hundreds of Health Centers and primary care associations for over 15 years to plan capital projects, finance growth, and identify ways to improve performance. We provide innovative consulting services and extensive technical assistance with the goal of supporting and expanding community-based health care. Additionally, Capital Link works in partnership with primary care associations, the National Association of Community Health Centers, and other entities interested in improving access to capital for Health Centers. For more information, please visit www.caplink.org.

About the National Association of Community Health Centers (NACHC):

Federally Qualified Health Centers serve over 22 million people at more than 9,000 sites located throughout all 50 states and U.S. territories. Because Health Centers serve patients regardless of their abilities to pay, they depend on public financial support and need a unified voice and common source for research, information, training, and advocacy. To address these needs, NACHC organized in 1971. NACHC works with Health Centers and state-based primary care organizations to serve Health Centers in a variety of ways:

- Provide research-based advocacy for Health Centers and their clients.
- Educate the public about the mission and value of Health Centers.
- Train and provide technical assistance to Health Center staff and boards.
- Develop alliances with private partners and key stakeholders to foster the delivery of primary health care services to communities in need.

As a founding partner of Capital Link, NACHC appoints some of Capital Link's board members. The two organizations work closely together on issues related to Health Center capital development and economic impact. For more information, please visit www.nachc.com.

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“Predicting the rain doesn’t count;
building arks does.”

– Warren Buffet, Investor

Introduction

The amount and availability of data in today’s health care environment is increasing on a daily basis. It can be collected, labelled, discussed, filtered, even bought and sold. But what can data actually do for us? The analysis of data is essential. It measures improvement, establishes trends, and can, at times, determine success or failure. Prior to advanced computer technology, the sheer size and ever-increasing availability of data made it difficult to construct and manage. Now, we are able to collect and compute vast amounts of information and develop innovative tools to monitor and track data, often automatically. As these tools become more sophisticated and more powerful, organizations have been able to evaluate management techniques and use data to impact operations. It appears that no industry is immune to these innovations, one of which is predictive analytics.

Using data and technology, organizations can now move beyond simply tracking the past to anticipating the future. Although common in many industries for years, the use of predictive analytics is now becoming more applicable to health care. Data collection efforts currently utilized by Federally Qualified Health Centers are only a starting point for what is necessary to be effective in improving patient care, reducing costs, and negotiating favorable contracts with payers. The use of predictive analytics to make and support business decisions is essential as a Health Center’s payer mix evolves and it becomes responsible for all patients attributed to it by Managed Care and Accountable care organizations (regardless if they are treated or not). A Health Center’s ability to engage with payers and understand which patients are more likely to seek inappropriate care or have a higher risk of having a chronic condition, and assist them in avoiding expensive hospitalizations and readmissions has become critical.

The purpose of this document is to:

- Define predictive analytics
- Provide an overview of its history and development
- Address the data and resources needed to predict a patient’s future behavior
- Identify how a Health Center can begin utilizing it
- Include specific examples of how it has been successfully used
- Clarify Health Centers’ understanding and expectations of predictive analytics

“Analytics today is at the point of high awareness and very little understanding.”

– Lana Klein, Co-founder, 4i

Overview of Predictive Analytics

Definition

***Predictive Analytics:** Technology that learns from experience [data] to predict the future behavior of individuals in order to drive better decisions.ⁱ*

Many of our decisions today are determined by what we know (or perceive to know) and are able to calculate ourselves. Choosing the route for the commute to work may depend on the day of the week, time of day, or weather. These are all variables we can reasonably track and calculate in our heads. More complex decisions require us to utilize basic computing such as online calculators. Yet as data has become easier to generate and collect, the amount stored has quickly begun to swell. Simultaneously, computing power and memory are rapidly advancing, contributing to further exponential growth.

Considering the number of variables and sources now available, we can no longer use typical desktop applications to adequately consider even a majority of the possible outcomes and the consequences of every action. Aided by advancing technology, such as machine learning¹, predictive analytics enables the modeling of actions and consequences that considers the vast number of possibilities, as well as a real-time estimate of the probability of their occurrence, allowing for better planning and management.

History

Predictive analytics is not a new concept. There have been developments in this field since the dawn of the computer age in the 1930s. One of the more celebrated early predictive analytic efforts was during World War II when Alan Turing used it to decode German messages.ⁱⁱ During the same period, the Kerrison Predictor was introduced. This machine was programmed to predict the flight pattern of enemy aircraft and aim weapons in the direction a plane was heading rather than where it was currently located.ⁱⁱⁱ Also during the 1940s, the world’s first electronic computer, ENIAC, was developed by the U.S. Army to compute ballistic firing tables.^{iv} Work around ENIAC yielded great technological advancements, including the first

¹ Machine learning focuses on the development of computer programs that can teach themselves to grow and change when exposed to new data.

weather predictions.^v In 1958, the credit bureau FICO accelerated predictive modeling by applying it to credit risk decisions. During the 1960s, the U.S. military began applying predictive analytics in testing potential employees for military assignments, taking personality and interests into consideration^{vi}. Then in 1973, the first model to predict optimal stock prices over time was introduced.

By 1995, both Amazon and eBay were online, striving to make online shopping a personalized experience. In 1998, Google first applied algorithms to web searches.^{vii} In 2003, Michael Lewis released *Moneyball*, a book about how the Oakland Athletics used predictive analytics to revolutionize professional baseball operations in the late 1990s. Now *Moneyball* is a term routinely applied to a business or management effort that utilizes data-driven predictions and planning.^{viii} In recent years, IBM has developed Watson, an analytical engine that extracts data from many sources in real-time^{ix}. The initial intention of Watson was to interact with humans on the game show *Jeopardy!*, which it did in February 2011 by outperforming two of the show's returning champions. IBM has continued to develop Watson, which now has a multitude of commercial uses, including Watson Health.^x

Modern technology brings a proliferation of advances in predictive analytics, including:

- Natural language processing where a computer 'listens' to speech and can respond verbally^{xi}
- Unstructured analytics that can 'read' notes in electronic health records (EHR) and make predictions about high risk patients as well as suggest diagnoses^{xii}
- Text analytics that decipher emotions from Twitter posts^{xiii}
- Workforce models that predict which employees might soon leave their position and who is likely to stay and why^{xiv}

Benefits

The potential benefits of predictive analytics are numerous and significant. From planning vacations^{xv} to determining when and where to have a spine surgery^{xvi}, predictive analytics can, and will, play a role in decision making. The benefits of predictive analytics for Health Centers include the ability to:

- Identify trends
- Understand patients
- Improve operational and clinical performance
- Drive strategic decision making
- Predict patient and staff behavior^{xvii}

With increasing responsibilities, patient needs, and payer expectations, along with reduced resources, Health Centers must consider any opportunity that improves efficiency. With predictive analytics' growing adoption, a Health Center can quickly find itself at a disadvantage by not utilizing or at least becoming aware of its potential capabilities.

Studies suggest that an investment in predictive analytics yields positive returns. In some cases, the return on investment (ROI) with predictive analytics has exceeded 200%, primarily due to a reduction in expenses rather than an increase in profit. A 2011 report by IDC^{xviii} concluded that the typical ROI for projects that incorporated predictive analytics was approximately 250%, while analyses that focused only on accessing information and internal productivity gains returned 89%. In 2012, Nucleus examined 60 analytics-related ROI case studies. It found that for every dollar invested in predictive analytics, business intelligence, and performance management products generated a gain of \$10.66, or an ROI of more than 1,000%. For example, the Internal Revenue Service created an improved model for flagging suspicious-looking tax returns. The previous model's success rate was just 1% of flagged returns that turned out to be cases of fraud. The new model improved the success rate to 25% and was credited with a return over several years of \$6 billion to \$7 billion.^{xix}

In health care, ROI is not measured by revenue but rather by the savings realized through reducing expenses, such as avoiding ER visits and other costly treatments. Recently, the University of Mississippi Medical Center cited a 400% ROI from a documentation and data visualization initiative focused on physician engagement. They have also recently integrated predictive analytics into the treatment of pressure ulcers, which is projected to save the institution between \$500,000 and \$1 million.^{xx}

Health Centers can utilize predictive analytics in a multitude of ways, furthering its consideration and implementation of patient engagement, patient compliance, chronic disease management, regulatory compliance, avoidable deaths, hospital readmissions, public health, waste and abuse, and health outcomes.^{xxi} And this is only the beginning. Clearly predictive analytics is in its infancy within health care, and the exponential pace of technological advancements will identify additional uses and benefits we have yet to consider.

Limitations

Predictive analytics does not claim to be magic or suggest it can solve all of an organization's ills. As with all management and analytical efforts, there are limitations to applying it to operations and planning. Predictive analytics:

- **Cannot predict the future:** Providing the probability of an event or behavior does not guarantee any specific occurrence or its timing.
- **Cannot change the past:** Utilizing partial or complete data reflecting the past to predict the future does not allow for the alteration of that data.
- **Cannot provide answers to questions not yet asked:** Successful predictive analytics requires that specific question(s) are posed prior to building models and seeking probabilities or it risks returning unrelated or irrelevant results.
- **Cannot create something out of nothing:** Predictive analytics require reliable, complete and appropriate data sets. Otherwise, models based upon random or incomplete data will produce moot probabilities.

- **Cannot always determine good data from bad:** While predictive analytics can be developed to predict the reliability of data, models typically assume that data provided is appropriate.
- **Cannot eliminate risk of failure:** Predicting the probability of an event is not a perfect science as it reduces margin of error, but does not remove it.^{xxii}

In addition to restrictions, the following limiting factors should be considered when developing and implementing changes in health care's data operations:

- **More data does not equate to more insight:** It can be difficult to extract robust and clinically relevant conclusions.
- **Insight and value are not the same:** While many solid scientific findings may be interesting, they do little to significantly improve current clinical outcomes.
- **The ability to interpret data is as varied as the data itself:** Sometimes even the best data provides only limited insight into clinical health outcomes.
- **Implementation may be challenging and must be balanced with the economic interests of the organization:** Leveraging large data sets successfully requires a health system to be prepared to embrace new methodologies. However, this may require a significant investment of time and capital.^{xxiii}

A Health Center's available resources and skill set are a key factor in successfully developing, implementing, and utilizing predictive analytics. While predictive analytics has advanced to a point where consultants, academia, EHR add-ons, open-source programming, and modeling software can assist with implementation, a productive program does require a dedicated level of time and skilled staff and/or partners.

Examples

The following examples illustrate the limitations of predictive modeling, which are often related to a shift in expectations:

Netflix, an avid and advanced user of analytics, announced in October 2006, that it would award a \$1 million prize to the first developer of an algorithm that could improve on its current customer predictions by 10%. In September 2009, Netflix awarded the prize to a team that delivered the model. That same year, Netflix announced a second contest that would also consider customers' demographic and behavioral data. However, soon thereafter, Netflix cancelled the second contest due to privacy concerns. In 2012, Netflix acknowledged it would not be implementing the winning model due to a significant increase in its membership since 2006 and the fact that it had shifted its primary service line from mailing DVDs to global online streaming.^{xxiv}

During World War II, the U.S. Air Force found that the interview process for identifying potential pilots could be reduced to a series of questions prior to assignment and training, thus reducing the amount of time and resources spent on inappropriate candidates.^{xxv} One of the questions included, “Did you ever build a model airplane that flew?” It was found that this one childhood experience indicated the interest and potential skill set needed to be a successful pilot in adulthood.^{xxvi} Google also tried this approach in identifying future computer engineers by asking applicants the following questions: “When did you get your first computer?” and “Did you ever make a computer from a kit?”^{xxvii} While these questions are helpful when included in a series, alone, Google’s questions were found to not be as effective as the Air Force’s pilot development question—perhaps due to the generational differences in education, available technologies, and diversity in computer-related experiences.

In 2008, Google began to explore the possibility of predicting flu outbreaks based upon searches through its website and launched Google Flu Trends. The expectation was that with the search data, in collaboration with Centers for Disease Control and Prevention (CDC), Google could predict the location and prevalence of flu outbreaks two weeks earlier than the CDC, thus saving significant resources and, not to mention, lives. However, in 2013, Google Flu Trends missed the peak of the flu season by 140%, which subsequently led to the termination of the program. Detailed analysis found that various Google searches related to seasonal terms, such as “high school basketball,” were mistakenly influencing the data. Also, because of the media attention the Google Flu Trend project and other health-related Google programs attracted, the search patterns had changed and became inflated and skewed.^{xxviii}

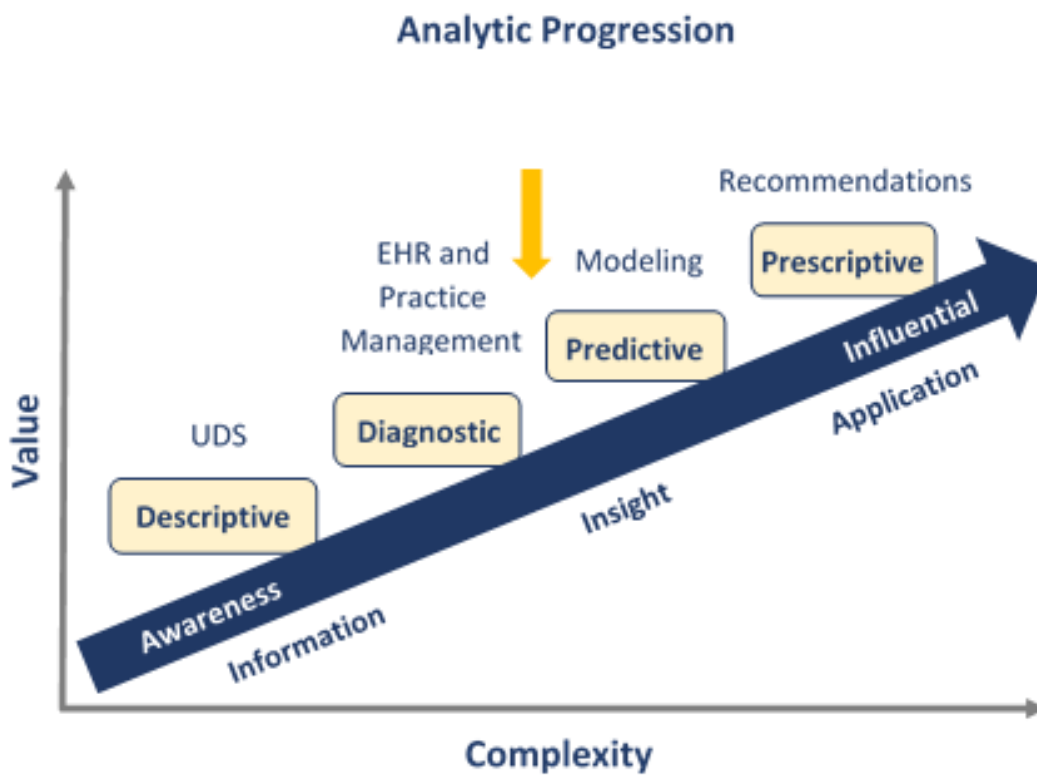
These examples illustrate the determination and, at times, the urgency to improve outcomes based upon what we know and what we want to know. Yet at the same time, they serve as a caution against oversimplifying results and making premature conclusions prior to validation.

“Data is the next blockbuster drug.”

– Chris Hogg, COO, Propeller Health

Healthcare Analytics Today

The chart below illustrates the progression of data measurement and collection to analytics and prediction. Many Health Centers are currently utilizing diagnostic analytics and are moving towards predictive analytics, indicated by the downward arrow. Traditionally, Health Centers are quite efficient in measuring, tracking, and reporting but have only recently reached a point of capacity and understanding to consider predictive and, eventually, prescriptive analytics.^{xxix}



Ongoing changes in healthcare delivery and financing systems are presenting challenges and opportunities for Health Centers.

Challenges	Accountable care challenges include deployment of new care management programs without access to timely, accurate, contextual, digestible, and high-quality data.
	Analytics challenges include data complexity, conflicting IT priorities, lack of understanding of analytics, lack of funding, identifying relevant data, and staffing.
Opportunities	A wide range of “use cases” (i.e., a list of actions steps defining the interactions between a role and a system to achieve a goal) for analytics in health care will benefit best practice development, outcomes analysis, prediction, and surveillance.

Challenges and opportunities can also be identified using the four attributes of analytics: volume, variety, velocity, and value.

1. **Volume of data:** Healthcare information will double in the next five years as a result of digitized medical information found in EHRs, access to unstructured data and data from mobile devices, remote patient monitoring devices, and social media.
2. **Variety of data:** For example, searching structured data for the smoking status of a patient may return the word "smoking" but no information on how much the patient smokes, and whether the patient is an active smoker or recently quit smoking. Analyzing unstructured data such as a doctor's notes allows healthcare organizations to establish context and more reliably extract predictors for readmission.
3. **Velocity of data:** Health Centers have historically used retrospective data for analytics, which is not timely enough to affect clinical decision support or interventions for patients with deteriorating health. Capturing real-time data from online monitors that include Apple’s ResearchKit, for example, is proving to be an effective means of detecting complications in established patients
4. **Value of analytics:** In a 2012 survey, 47% of healthcare provider respondents indicated they did not know how to measure the value of analytic investments. Accountable care requires timely, accurate, contextual, digestible, and high-quality data to meet the requirements of improving the patient experience, controlling costs, and improving the health of the population. Health Centers are typically late adopters of new technology, and that is also the case for analytics. As more use cases become available, demonstrating the power and opportunity of analytics, healthcare organizations will begin investing more heavily.^{xxx}

Examples of Predictive Analytics in Health Care

Below are a few examples of the numerous implementations and experiences around predictive analytics in health care:

Adding frequently updated EHR data to the Centers for Medicare and Medicaid Services (CMS) standardized Minimum Data Set (MDS) for nursing home patients increased the accuracy of a predictive analytics algorithm by more than 10% making it easier to reduce or prevent the costs and impacts of falls among elderly patients.^{xxxix}

A director of care management at a 20,000-patient hospital uses predictive analytics daily to see which patients are at greatest risk for readmission. On the day the patient is discharged, staff can see information on the risk of that person being readmitted or going to the emergency department. This use of analytics replaces a nurse's half-hour patient discharge interview and provides better predictions and outcomes.^{xxxix}

Researchers are using routinely collected EHR data as the fodder for an algorithm that gives clinicians an early warning about sepsis, which has a 40% mortality rate and is often difficult to detect.^{xxxix}

A risk score developed by researchers in 2013 allows clinicians to predict the likelihood that diabetic patients will develop dementia in the future.^{xxxix}

The U.S. Army is attempting to curb the rampant rate of veteran suicides by leveraging a predictive risk model to identify patients who may be likely to harm themselves.^{xxxix}

Research conducted on patient activation scores¹ accurately predicted the use of two costly services three years later. Patient activation scores were first measured in 2011. A year later, it was found that for patients with the highest level of activation compared with those at the lowest level hospitalization costs were 38% lower (\$12,467 vs. \$7,714) and ED costs were 37% lower (\$1,126 vs. \$711). Three years later, the difference in hospitalization costs between the two groups was 29%, and the difference for ED costs were 28%.^{xxxvi}

In addition to having already acquired three other data companies, IBM announced in February of 2016 that it was purchasing Truven Health. This and other acquisitions will provide IBM with a repository of health data for approximately 100 million patients from thousands of hospitals, employers, and state governments and double the size of IBM Watson Health to 5,000 employees. IBM will now inform benefit decisions for one in three Americans and have the ability to better manage populations of patients within the evolving value-based market.^{xxxvii} Shortly after this announcement, IBM revealed plans to invest up to an additional \$150 million over the next several years in its first European Center of Excellence. Located in Italy, this Center will bring together data scientists, engineers, researchers, and designers to develop a new generation of data-driven healthcare applications and solutions.^{xxxviii}

¹ The Patient Activation Score or Measure (PAM) is a commercial product which assesses an individual's knowledge, skill, and confidence for managing one's health and health care.

“Managers tend to pick a strategy that is the least likely to fail, rather than to pick a strategy that is most efficient.”

– Michael Lewis
Moneyball: The Art of Winning an Unfair Game

Implementation Considerations

Most Health Centers ask the following common yet appropriate questions when presented with a new idea that requires precious time and resources in return for possible but significant rewards:

- How much will this cost to consider, implement, and utilize?
- Who would be responsible on an ongoing basis?
- How much benefit will my organization and patients realize?
- Who else is using this?
- What are their results?

With the advancement and expansion of processes, tools, applications, and expectations, it is understandable to be overwhelmed, or at least puzzled, by the potential of predictive analytics. There are a multitude of ideas, concepts, and explanations to wade through when learning about and evaluating such a topic. The two likely initial questions are: “How do I get this?” and “Who is responsible for this?”

Accessibility

While the purpose of this report is not to provide instruction on how to construct predictive models, a description of some of the available resources is provided for awareness and reference. Numerous consultants, open source software, off-the-shelf applications, population health software, EHR add-ons, and academia are the primary sources of development.

Well-known software and data companies such as FICO, HP, IBM, Microsoft, and Oracle have the capacity to provide sophisticated modeling and guidance, but usually at a significant price. However, there are now several newer companies that have been established with the sole purpose to provide analytics. When choosing to work with an analytics service provider, Health Centers should consider their own capacity and goals prior to implementation. Once the potential ROI for a predictive analytics model is estimated and the specific goal of the model solidified, appropriate resources may be identified.

While open source and/or freeware software, such as Orange, R, RapidMiner, and Weka, can be easily obtained and accessed, development of the skills needed to utilize and implement these programs is usually labor intensive. Commercial software, on the other hand, may be easier to

implement since the tutorials are usually more focused on the end user' experience. Such packages include Enterprise Miner, Mathematica, SPSS Modeler, Stata, and Statistica.

Often, predictive applications can be found within popular software packages that Health Centers may already own. For example, Microsoft offers Power BI for Office 365 that enables Excel to conduct advanced time series analysis for forecasting. Another example is Google's cloud-based machine tools, Prediction API, empowering users to utilize several pattern-matching and machine learning applications.

Electronic Health Records

Most, if not all, EHR vendors now provide services that include some level of analytics as part of their standard product or as an add-on. Because of its data-rich environment, an EHR can be an ideal place to begin when developing any predictive model. There are several benefits to using EHRs in such an effort, including:

- **Analytics that include data reflecting the Social Determinants of Health (SDOH) support efficient diagnosing.** With the ongoing attention being paid to the SDOH, incorporating environment and demographic information with clinical information data can provide more accurate diagnoses in addition to identifying nontraditional but significant drivers of health.
- **Combining disparate data types creates opportunities to strengthen financial planning.** Although it is possible, productive, and perhaps ideal to incorporate various data sets such as patient records, patient surveys, financial records, and payer information into a predictive model, the challenge may lie in how to access such diverse data from various sources. Estimates for data preparation in many predictive models can be as high as 95% of the total modeling development.
- **Tracking patient flow enables productivity improvements.** By mapping clinical and operational touch points for each patient engagement, Health Centers that have real-time analysis can enable modeling to identify bottlenecks and the steps in the process that need the most improvement.
- **System performance is enhanced in an interconnected world.** Information in an EHR can come from diverse sources, hospitals, prior providers, payer, and other organizations, and should be analyzed to determine the best collection methods and usefulness in modeling.
- **Comparing your organization's performance to peers and national standards.** This information allows you to discover strengths and weaknesses in your operation.^{xxxix}

Predictive analytics from an EHR can also influence value-based payment reform. As Health Centers consider value-based payments, the ability to capture data at multiple points and share that data and understanding with key partners will be valuable. Payment reform is essentially better risk management requiring greater data integration and analyses.^{x1} Whether the focus is on hospital readmissions, claims management, participation within an Accountable Care Organization (ACO), an Independent Practice Association (IPA), or negotiating with a Managed Care Organization (MCO), a Health Center's data will be the basis of that relationship and any

opportunity to predict the probability of a patient's or contract's outcome will be vital to that Health Center's success.

Workforce

Workforce modeling can predict recruitment, retention, and any anticipated shortage of skills in the marketplace. Recent estimates have valued the predictive analytics' market at \$6.5 billion within a few years, which would lead to an estimated U.S. shortage of 140,000 analytics experts. LinkedIn's latest number one "Hottest Skills That Got People Hired" is "statistical analysis and data mining."^{xli} Last year, the median salary of a junior level data scientist was \$91,000, and for those managing a team of 10 or more it was well over \$250,000. As a result, additional educational programs have been introduced and there are now over 100 graduate programs worldwide.^{xlii}

If analytics staff are difficult and expensive to secure, how are most Health Centers going to be able to involve themselves in any level of analytics? There are efforts in place to determine if non-data scientists could and should be able to build and interpret predictive models. The idea is with the development of user-friendly predictive products and a shortage of experienced data scientists there may be appropriate cases where business intelligence staff could perform certain tasks associated with predictive analytics. The most frequent errors thus far from non-data scientists is misinterpreting the data and using variables derived from the target variables thus creating a type of self-fulfilling prophecy. To overcome such tendencies, some companies have data scientists and business intelligence staff collaborate as a team.^{xliii} This concept seems quite similar to Patient Centered Medical Home (PCMH) teams and would likely address a little talked about concern—communication between those that build predictive models and those that manage based on the findings. Health care managers and providers do not typically have a background in analytics and software development, and likewise, analysts and software developers rarely have a clinical background. This is typical in most industries where operational leadership relies on the results of information technology but does not necessarily understand the underlying structure. Leadership should ensure their decisions are based upon results calculated by data managers or "analytical translators"^{xliv} who have at least a general understanding of basic operations, questions posed by leadership, data definitions, and possible impact of results.

While the size of the organization or data may not be the primary factor in determining whether or not to explore predictive analytics, the capability of a Health Center, PCA, HCCN, IPA, and ACO is certainly important. The capacity to ensure data validity and security, compare models, invest resources, calculate return on those investments, implement pilots, provide ongoing monitoring, etc. is not to be taken lightly. As with other change or pilot implementations, an organization may want or need to consider a collaboration to provide economies of scale or shared resources. Finally, whether acting alone or collaborating with partners, a commitment to staff development and/or outsourcing will be required.

“Once you develop a model, don’t pat yourself on the back just yet. Predictions don’t help unless you do something about them.”

– Eric Siegel, Ph.D., Founder, Predictive Analytics World; President, Prediction Impact

Applications by Community Health Centers

For Health Centers that collect significant amounts of data on patients as well as operations, there are several potential predictive methods with attractive outcomes worth considering. The steps of predictive analytics modeling are similar to other project management techniques. The following flow chart presents the basic steps for modeling.



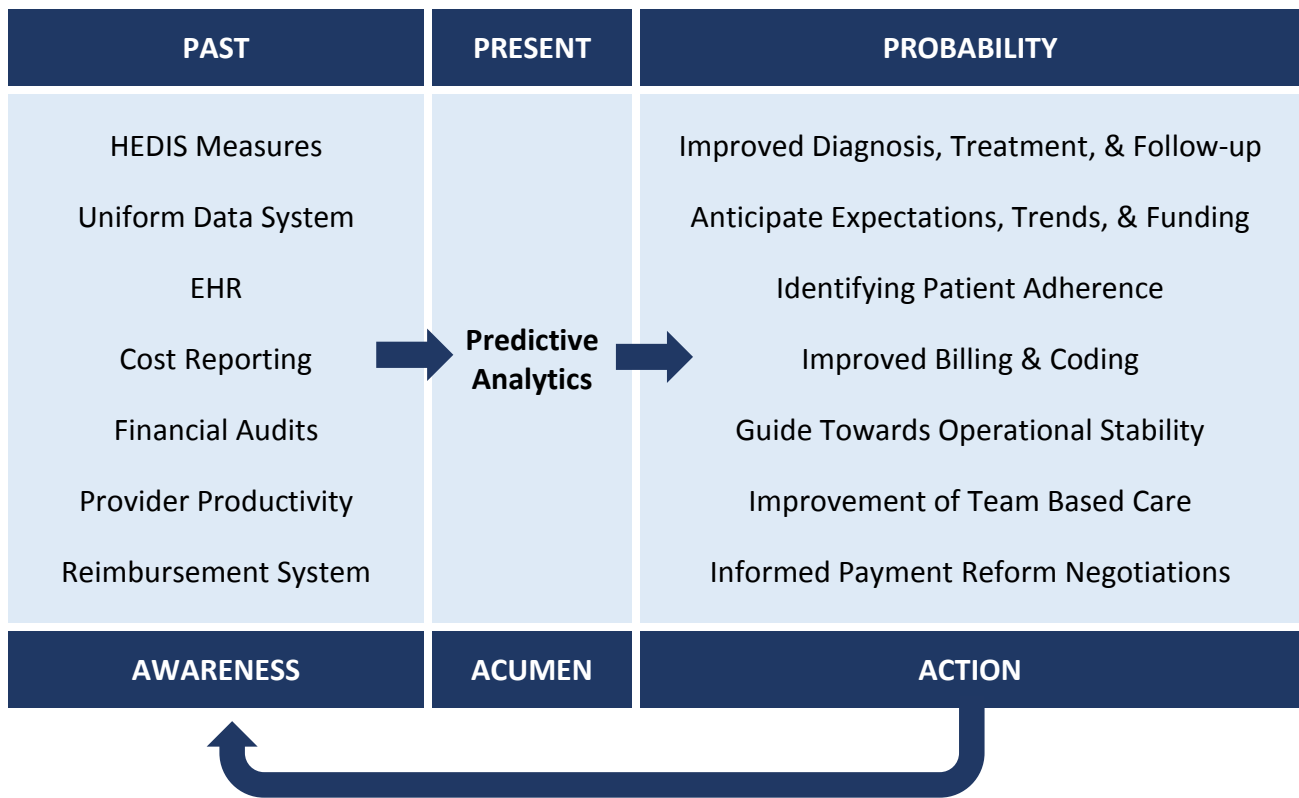
Each step is likely a familiar concept to Health Centers. Taken individually, in order, and within context, most centers will be able to consider, utilize, and realize the benefits of predictive analytics.

While Health Centers have much to gain from such efforts, again, several considerations should be addressed early in the process:

- **Hype:** Is this process appropriate for the Health Center and its patients, or is there pressure to participate due to the compelling attention surrounding analytics?
- **Workforce:** Is there someone on staff that can conduct initial evaluations and possibly develop models, or will these skills need to be outsourced? What is the expected budget and ROI?
- **Data Collection:** How is data currently gathered? Is the data stored locally, remotely, in the cloud, etc.? How will new formats and sources of data, such as wearable technology, telemedicine, unstructured EHR data, and home monitoring be addressed? Who owns the patient and operational data? Is this data accessible for use in predictive modeling?
- **Security:** Is the data system secure from external attacks and internal disruptions?
- **Cost and Capacity:** Is there sufficient software, time, staff, and incentive to explore further analytics?

These considerations should not prevent Health Centers from evaluating and pursuing predictive analytics, but they should prepare the organizations for various commitments, timelines, and expectations.

The chart below contains a list of current reporting requirements for Health Centers. If this existing data is processed through a predictive analytic model, the results could provide guidance to improve operations and outcomes.



Examples

The following are examples of Health Centers and health systems that have successfully implemented analytics.

ARcare, a Health Center that serves Arkansas and western Kentucky, created an analytic algorithm within their EHR that identifies patients with the highest risk of hypertension. Thus far, the organization has been somewhat surprised to find that the majority of patients with undiagnosed risk have been Caucasian women between the ages of 18 and 39 with few indicators of obesity or depression. ARcare anticipates expanding such analytics to increase patient participation, improved payer negotiation, “data participation” with clinical teams, and enhanced need identification by geography.^{xiv}

HealthLinc, an Indiana Health Center, relies heavily on data. It has an EHR with analytics capabilities and a staff engineer to write reports. HealthLinc recently began working with a consulting partner with a population management software. Now, data is readily accessible to the clinical care team. Health Center management said they feel lucky to have had someone on staff suggest piloting this approach, which has improved the health of the community. The next big step will be to further improve patient engagement. The current software allows them to do so by constructing Venn diagrams and identifying patients that fall within multiple indicators. HealthLinc now plans to look closer at the patients just outside the Venn's center who, for instance, may have diabetes, but perhaps do not currently have hypertension or depression. After identification, HealthLinc will attempt to improve the preventive behaviors of those patients. Another next step is to combine these resources with claims data. HealthLinc emphasized that if and when that data is analyzed alongside data from a social determinants of health project currently in process, the organization will be able to determine if high utilizers have transportation, economic, and environmental barriers.^{xlvi}

Using natural language processing technology, Carilion Clinic was able to identify 8,500 patients throughout their Virginia-based hospital system who were at risk of developing congestive heart failure within the next year. The pilot project took only six weeks to complete. They began by gathering three years' worth of data belonging to 350,000 patients. In addition to more than 200 factors, such as blood pressure, beta blocker prescriptions, and weight, it combed through more than 20 million notes, uncovering nuggets of information that are typically not entered into medical records. These notes include the number of cigarette packs a patient smokes, the pattern of prescriptions, and how well the heart is pumping. Additional details were that might have initially escaped a medical history or visit, such as a patient's social history, depression, and living arrangements, were also included. The resulting predictive algorithms almost immediately reduced the 8,500 patients to 5,000 and are now processing the information, which scores a patient's risk, to its healthcare providers.^{xlvii}

“It is far better to foresee even without certainty than not to foresee at all.”

– Henri Poincare, *The Foundations of Science*

Models and Methodology

There are as many predictive analytic models as there are interests in the results. While this document is not intended to provide deep understanding in the actual coding and development of predictive analytics, the following examples are provided as a glimpse into efforts directly involving Health Centers, their data and their operations.

HRSA’s Predictive Model Generation

In December 2014, the Department of Health & Human Services’ Office of Program Integrity Coordination (OPIC) hosted a meeting in partnership with Health Resources and Services Agency (HRSA) regarding IBM’s exploration of the potential of predictive analytics for the modeling of Health Center operations. The project was divided into three phases: Data Foundations, HRSA Predictive Model, and Expansion to Other Discretionary Grants. In this initial meeting, a summary of Phase 1 (July-November 2014) was presented.

The data set contained over 5,900 annualized records of Health Center grant recipients for years 2010 through 2014. Each record had over 250 variables; of those, IBM selected a subset of meaningful predictors that may identify and predict the level of influence specific drivers had in Health Center operations. Those drivers and their corresponding variables are provided below.

Key Drivers	Sample of Variables
Financial Capacity	Audits results, drawdown status, changes in profit, costs per patient
External Environment	Ratio of Full-Time Equivalent (FTE) per patients, changes in patients, FTE
Leadership	Same CEO and/or clinic director
Expansions	New grantees, changes in total grant amount
Progressive Action Conditions	Total conditions, those that frequently got to 30 days, measures of time to resolve conditions
General Grantee Characteristics	Urban/Rural

The initial review of potential predictors suggested significant correlations between specific drivers and Health Center performance.^{xlvi} Those with Health Center experience might consider many of the findings to be somewhat obvious, but having the statistical significance of these variables within these drivers can lead to the improvement in specific aspects of operation, reduction of expenses due to “trial and error,” and improvement in funding decisions.

In July 2015, a meeting regarding Phase 3 was held to provide an overview of OPIC’s further exploration of predictive analytics in reducing risk for discretionary grants. A pilot was developed in order for HRSA to examine which Health Centers might later experience compliance issues. The model applied a data-driven approach to discretionary grantee risk across the population, complementing the expertise from detailed grant-level analysis. The model further confirmed prior understanding of grantee risk regarding drawdown restrictions and audits, and encouraged ongoing current processes of monitoring and interaction. Additionally, the models revealed new sets of predictable risk factors that could be used by HRSA, such as changes in leadership, drawdown behaviors, and trending of revenues and patients.^{xlix}

Predicting Financially Strong Health Centers

Using an idea derived from Capital Link’s January 2016 publication, *Hallmarks of High Performance: Exploring the Relationship between Clinical, Financial and Operations Excellence at American’s Health Centers*,¹ a predictive analytic model was constructed around Health Centers that had been awarded one of HRSA’s Quality Improvement Grants in 2014 (<http://www.hrsa.gov/about/news/2014tables/qualityimprovement/>), and which are considered to be the most financially sound. This basic predictive analytic model consisting of publically available 2014 UDS indicators was developed on Statistica software. Its initial findings indicate that perhaps the size of a Health Center is important, given the model’s 95% success rate in determining which Quality Awardees might be considered stronger financially by the number of patients treated within that year. Other strong indicators included payer mix percentages, payer proportionality, the percentage of providers involved in enabling services, staffing mix, and costs per patient. Indicators that did not seem to dictate a Quality Grantee’s financial strength included the actual number of Medicaid and self-pay patients and growth rates in certain types of patients.

This overly simplistic model serves only as an example for reference and contains several assumptions that should be pointed out here and further addressed in any future models. The determination of which organizations might be financially strong was loosely based on financial indicators and ratios and not determined by any specific benchmark, the data set was limited by those centers who had received a Quality Improvement Grant, and any model should have multiple comparisons developed in parallel to avoid any bias. It should also be noted the data collection took several days, the data preparation took several hours, and the building of the predictive analytic model required a few hours and then minutes to run. This experience is typical of most predictive analytic efforts. Nevertheless, one can easily recognize how this type of information could certainly improve a Health Center’s planning, negotiations, implementation, and operations.

“The best way to predict the future is to invent it.”

– Alan Kay, Computer Scientist, *Financial Times*, November 1, 1982

The Future of Predictive Analytics

When the ENIAC computer was developed in the 1930s, it weighed 30 tons and occupied 1,500 square feet.^{li} In 1995, the system was re-implemented on a tiny computer chip that could fit in the palm of a hand.^{liii} There is little evidence that ENIAC’s inventors were aware of where their creation would lead. Similarly, predictive analytics has its own rich history, yet ironically cannot predict its own future.

As technology and reform continue to encourage and enforce further efficiencies, predictive analytics will continue to play a significant role in many aspects of both our personal and business lives:

- Analytics education curriculums will continue to be developed and integrated into existing programs and degrees, such as engineering and computer science. There will also be opportunities for employees who have the interest and aptitude to learn on the job.
- There will continue to be a shortage in the workplace of those with appropriate analytic skills, at least in the short term. Until those who are currently entering analytics programs emerge, there will likely be a high demand for additional availability and skills. In the meantime, it is possible that predictive analytics may technologically advance to the point that such a high level of skill may not be required to develop and operate most models.
- Improvements, such as automation, will continue until predictive analytics is a seamless part of many strategic planning and management plans. As was the case with Geographic Information Systems (GIS) 15 to 20 years ago, once the incentives and costs matched the technological advances, GIS mapping was easily accessible to everyone—online, in cars, on mobile phones, etc.
- Expectations will begin to match benefits, costs, and experiences. With the continued influx of workers, investments, and possibilities, in addition to the media coverage, it is doubtful predictive analytics will simply find itself obsolete anytime soon. It will further evolve with technology and media into prescriptive uses that attempt to foresee and influence changes in behaviors.

Examples

As expected with this type of growth and evolution, there are efforts underway to establish structure and standardization for predictive analytics. The following are just two examples of such efforts:

The Predictive Analytics Reporting (PAR) Framework was born out of an initiative supporting education with evidence through community development and collaboration. PAR provides members with predictive analytics, national outcomes benchmarks, and intervention measurement.^{liii}

The expansion of EHR data is enabling a similar expansion of electronic health care predictive analytic (e-HPA) applications. The development and application of e-HPA is to ensure that the field develops in a scientifically sound, ethical, and efficient manner. To achieve these objectives, 17 experts with diverse expertise including methodology, ethics, legal, regulation, and health care delivery systems, assembled to identify emerging opportunities and challenges of e-HPA and propose a framework to guide the development and application of e-HPA. The proposed framework includes three key domains where e-HPA differs qualitatively from earlier generations of models and algorithms (Data Barriers, Transparency, and Ethics) and areas where current frameworks are insufficient to address the emerging opportunities and challenges of eHPA (Regulation and Certification, and Education and Training). The following list of recommendations summarizes the key points of the framework:

1. **Data Barriers:** Establish mechanisms within the scientific community to support data sharing for predictive model development and testing.
2. **Transparency:** Set standards around e-HPA validation based on principles of scientific transparency and reproducibility.
3. **Ethics:** Develop both individual-centered and society-centered risk-benefit approaches to evaluate eHPA.
4. **Regulation and Certification:** Construct a self-regulation and certification framework within e-HPA.
5. **Education and Training:** Make significant changes to medical, nursing, and paraprofessional curricula by including training for understanding, evaluating, and utilizing predictive models.^{liv}

To further solidify its prospects, predictive analytics has now become a source of fun and competition as well as an operational tool. With our environments now inundated with data, measurements, and games, there are several contests that provide opportunities to address problems in education, health, industry, and research.^{lv} Even the federal government supports such events annually through Challenge.gov, a one-stop shop that has prompted tens of thousands of individuals, including engaged citizens and entrepreneurs, to participate in more than 400 public-sector competitions with more than \$72 million in prizes.^{lvi} The Federal Office of Science and Technology Policy issues the annual Implementation of the Federal Prize Authority Progress Report outlining prize competitions to spur innovation, solve tough problems, and advance (all agencies') core missions.^{lvii}

Even with its relatively short history, predictive analytics has quickly become one of the more promising innovations of our day. As it continues to evolve, the power to predict individuals' behavior within a group offers the chance to not only better understand our lives and those around us but to significantly improve them.

Additional Resources

The following resources are for reference only and are not meant to be an endorsement of any company, service, and/or product.

Articles/Research

When a Health Plan Knows How You Shop

New York Times, June 28, 2014

http://www.nytimes.com/2014/06/29/technology/when-a-health-plan-knows-how-you-shop.html?_r=0

Preparing Analytics for a Strategic Role:

Behind WellPoint's Shift to a New Provider Payment System

Michael Fitzgerald, MIT/Sloan, April 2014

<http://sloanreview.mit.edu/case-study/preparing-analytics-for-a-strategic-role/>

A Predictive Analytics Primer

Tom Davenport, *Harvard Business Review*, September 2014

<https://hbr.org/2014/09/a-predictive-analytics-primer>

The Analytics Mandate

David Kiron, Pamela Kirk Prentice, and Renee Boucher Ferguson

MIT/Sloan, May 2014

<http://sloanreview.mit.edu/projects/analytics-mandate/>

Videos

Introduction to Predictive Analytics

Eric Siegel, Ph.D., UC Irvine Extension

<https://www.youtube.com/watch?v=DJS-WvHmoB0>

Why is predictive analytics important?

Eric Siegel, Ph.D.

<https://www.youtube.com/watch?v=CH8pMZMaIC8&authuser=0>

IBM Watson Health: How It Works

IBM Watson

<https://www.youtube.com/watch?v=Xcmh1LQB9I>

Why Data Matters: Moving Beyond Prediction

Jai Menon

<https://www.youtube.com/watch?v=VtETirgVn9c&authuser=0>

Big Data Analytics and the Transformation of Healthcare

Dr. Marty Kohn

https://www.youtube.com/watch?v=NhO-mNb_Lqw

Websites

IBM Watson Health

<http://www.ibm.com/smarterplanet/us/en/ibmwatson/health/>

KDnuggets

Collection of resources, data, education, etc.

www.kdnuggets.com

Kaggle

Data science competition community

<https://www.kaggle.com/>

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