Predicting Hospital Capacity and Efficiency

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Abstract: Hospitals and healthcare systems are challenged to service the growing healthcare needs of the population with limited resources and tightly restrained finances. The best healthcare organizations constantly seek performance improvement by adjusting both resources and processes. However, there are endless options and possibilities for how to invest and adapt, and it is a formidable challenge to choose the right ones. The challenge is that each potential change can have far reaching effects. This challenge is exacerbated even further because it can be very expensive for a hospital to experience logjams in patient movement. Each and every change has a "ripple" effect across the system and traditional analytics cannot calculate all the ramifications and opportunities associated with such changes. This project uses historical records of patient treatment plans in combination with a virtual discrete event simulation model to evaluate and predict capacity and efficiency when resources are added, reduced or reallocated. The model assigns assets as needed to execute the treatment plan, and calculates resulting volumes, length of stay, wait times, cost. This provides a valuable resource to operations management and allows the hospital to invest and allocate resources in ways that maximize financial benefit and quality of patient care.

1 INTRODUCTION

Hospitals and healthcare systems, especially US-based academic healthcare institutions, are under constant pressure to streamline and achieve more with limited resources and finances. With the growth of electronic medical record systems (EMRs), health-care data warehouses, and business intelligence technologies, there is more information available to identify problems and opportunities for improvement. For example, we have robust dashboards which show length of stay for patient cohorts and how these values compare to benchmarks. We have information around patient time in "boarder" status, i.e. being boarded in one department when they belong in another. Examples include patients in the emergency department (ED) who have been admitted to the hospital, patients in surgical recovery rooms who are no longer under the effects of anesthesia, and patients in intensive care units (ICUs) who no longer require critical care. We have information from patient-reported data, clinical engineering interfaces, staff time and attendance, and patient surveys. There is a staggering and growing amount of data available.

The challenge though is to use all this information to make good decisions and initiate valuable change. We can create change by adding or reallocating resources and by changing processes. Resources that could be adjusted include staff and staff schedules, beds and bed accommodations, operating rooms (ORs) and OR allocation schedules, imaging resources, clinic and ambulatory surgery locations, staffing and hours and more. Example processes that can be manipulated include: house and bed management; ED registration, triage and rooming procedures; preventive care initiatives; isolation process; discharge procedures; care management protocols; and urgent care facilities. It is challenging enough to predict the cost and return on investment (ROI) from such changes to make educated decisions. However, what really makes the challenge difficult is that each change can have far-reaching effects. For example, adding ED resources could create a logjam of ED patients waiting for an inpatient bed, or cause significant congestion in inpatient departments. Adding an OR room or adjusting operating schedules can create problems placing patients after perioperative recovery. Even a simple change like

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adjusting discharge order times can create a logjam of patients waiting for the orders to be processed. The challenge is exacerbated because it can be very expensive for a hospital to experience logjams in patient movement. For example, an admitted patient who is still in an ED bed is acquiring additional cost without compensation, and very likely getting reduced care. A patient occupying a regular bed, but requiring critical care treatment, is not only receiving reduced treatment, but is also creating additional staff requirements for the non-critical care department. Even small changes such as housekeeping procedures or staffing can have far-reaching effects across the hospital system.

In addition to the operational challenges above, there are both opportunities and risks for the actual clinical treatment of the patient. It is important to ascertain that any change in process or staffing does not reduce care. Generally, we measure quality of care by key performance indicators (KPIs) including readmission rate, mortality rate and rate of hospital-acquired infections. Additionally, disposition should be included to indicate that a discharge to home is a better outcome than dispositions such as discharge to skilled nursing facility. Finally, patient experience (customer satisfaction) results can be included.

Additionally, treatment processes can be improved. These include disease-specific clinical protocols such as initiatives for sepsis, exacerbated chronic obstructive pulmonary disease (COPD), congestive heart failure, pneumonia and stroke. There are also initiatives around specific clinical events such as ventilation, blood transfusions (McGlothlin 2017), administration of broad spectrum anti-biotics, management of central lines and catheters. Each of these can have far-reaching effects. For example, improving ventilation protocols can reduce reintubation and instances of ventilator-acquired pneumonia, and can result in reduced readmissions to ICU units. A significantly successful clinical program can increase the stress on the hospital by increasing the survival rate and putting pressure on lower acuity units to absorb more patients.

There is simply no meaningful way for anyone to manually determine all the possible ramifications, both positive and negative, from a change in resource allocation, process or treatment. In this project, we are proposing a digital simulation model which coupled with bio-statistics can provide much more meaningful and actionable insight.

2 BACKGROUND

In our investigation and design of this project we looked at literature and industry use cases surrounding:

- Predictive analytics in hospitals
- Tools for what-if scenarios for healthcare models
- Predictions models in other industries

Discrete event simulation is the process of creating a digital model of specific events and rules. Every treatment or movement in a hospital can be considered an event. Tools and systems for discrete event simulation are sometimes referred to as "digital twins". Digital twins create a complete virtual model of a physical asset or process, and can be networked together. Discrete event simulation and digital twins are not new technology. They have been used for years to simulate events that are too hard to test manually (Fishman 1978), such as the impact of heat or wind speed on a plane (Tuegel 2011). Also, they are used to simulate entire systems which are connected by well-defined rules. For example, they could be used in automobile manufacturing to determine if there is a cost advantage to a more expensive paint which dries more quickly (Grieves 2014). This would be based on the capacity of the additional manufacturing systems to absorb additional auto capacity more rapidly. There are many commercial digital twin products available on the market, as well as open source products such as Ditto (Glocker 2017) and OMNet++ (Varga 2001) and SimJava (Howell 1998).

Despite the long history of this technology, it has become much more mainstream in recent years. Digital twins were recently identified by Gartner as one of the ten significant trends of 2017 (Gartner 2017). The reason for this sudden grown is IoT (the internet of things). As there are more small devices connected to the network, and so much is known about these devices and sensors, there is more opportunity for digital modelling.

Despite the growth of this technology, it has rarely been applied to healthcare, which is a much less predictable model. A patient treated quickly and politely may still decide to leave the hospital against medical advice. A healthy patient might suddenly have a totally unexpected aneurism. A patient whose life was just saved may still be bitter and unsatisfied. Despite being optimally staffed for a normal Friday night, any particular Friday night may have an unforeseeable catastrophe such as a mass shooting or an earth quake. System-wide predictive analytics in healthcare is always challenging and discrete event simulation models are no exception.

The other reason IoT has accelerated the emergence of digital twin technology is because it provides real and discrete information. One of the major drawbacks of the digital twin approach has always been that it relied on the correct modelling of the business process. Hospitals and clinicians are often adapting to emergencies or unusual events and standardized processes are hard to develop or monitor. IoT allows us to do things like monitor actual staff and patient movement, clinical instrumentation and other true sources of data to infer business processes and outliers which were previously hard to realize.

In specific contexts, there has been significant work on predictive analytics in healthcare. Sutter Health was able to accurately predict 30 day readmission rates and leverage the information to target and reduce readmissions (Ng 2014) (Jamei 2017). Similarily, (Bardhan 2014) was able to predict readmission for congestive heart failure after analysis of data from 67 hospitals. Parkland Hospital has been able to accurately predict daily census and several hospitals have used similar technology to improve coding and reimbursement (Bradley 2010). (Maguire 2013) describes a successful predictive data mining project specific to diabetes. There are countless more examples, and we have tried to leverage what worked for them, but they tend to be limited to specific patient cohorts and single data points. While digital models for hospitals has been widely discussed, we were unable to find a successful system-wide project in the literature.

3 PROPOSED APPROACH

We will detail the implementation plan and phases for our project in section 5 after describing our specific requirements in section 4. In this section, we will just give a quick overview of the approach.

The general approach is to:

1. Extract patient treatment plans from historical encounters. These treatment plans must separate what is necessary to heal the patient from what happened in the historical encounter due to hospital inefficiency or capacity. We use biostatistical analysis to transform actual events into a treatment plan for that patient.
2. Model the resources and allocation rules based on the business processes of the hospital. This process will include both interviewing subject matter experts about the processes and profiling the historical data to infer and validate the proposed business rules.
3. Create a discrete event simulation model which places random patients into the hospital according to historic trends and then assigns resources to the patients according to their treatment plan
4. Collect statistics around the encounters as they pass through the model hospital.
5. Repeat the randomization many times to determine both the median values for length of stay, volume and other KPIs, and also worst and best case scenarios and the probability of significant logjams.

Once this is done, this model will support adjusting the resources and allocation rules, adjusting the treatment plans, and adjusting the patient flow based on market analysis and trends. Each of these creates a what-if scenario analyzed with the same system above, and multiple changes can be done in the model together to evaluate an entire proposal.

4 REQUIREMENTS

Before we outline our solution and implementation plan we need to more clearly identify the requirements for the system.

4.1 Measures

The following list of measures and KPIs was identified by our Operational Excellence team. The goal is that the solution will be able to accurately predict each of these measures.

- Throughput and Volume
  - Length of stay (total and in each area)
  - Volume (ED, OR, and transfer)
  - External transfer acceptance rate
  - Isolation patient days/hours
  - Census by hour and type
  - Discharges by hour
- Wait times
  - Boarding time (ED, ICU and OR)
  - Discharge order to discharge
- Utilization and Productivity
  - OR utilization
  - Staff productivity
  - Ancillary utilization including imaging, labs, pharmacy, telemetry
  - Bed Utilization
- Finances
  - Contribution margin
  - Activity based costs

   - » Cost per discharge
- Patient and clinical Metrics
   - » Readmission rate
   - » Mortality rate
   - » Wellness scores
   - » Patient experience scores

Each of these measures we will want to look at by specific patient cohorts based on diagnosis, payor, unit, day, time, location, procedure, age, etc.

4.2 Assets and Resources

The goal is that this project support what-if scenario analysis based on adding or removing resources or changing schedules. The following is the list of such resources determined so far:

- Beds
  There can only be one patient in a bed at a time. Whether a bed is appropriate for a patient is based on patient class (inpatient, outpatient, observation), level of care (such as ICU, intermediate, acute) and service (specialities such as cardiology or neurology). ED beds support combination of acuity and age.
- Rooms
  Rooms include one or more beds. Multiple beds in the room can only be filled if the genders and isolation status of the patients matches. For example, we cannot place a patient with clostridium difficile colitis (C. diff) with a patient who does not, without risking serious harm to the other patient. Isolation is managed in our system with specific orders.
- Staffing
  Staffing includes nurse and physician staffing by unit, anesthesia staff, pharmacy staff, imaging staff including technician and radiologists, housekeeping staff, transport staff, and ancillary staff including labs and pharmacy. Staffing volume can be adjusted by hour, unit or location.
- Operating Rooms
- OR hours
  The operating rooms support various volumes of staffed rooms at different times and days of the week. Moreover, there are primetime hours set by day of week and location. Non-emergent surgeries are delayed until prime hours.
- OR service block allocation
  Our hospital holds operating rooms for specific services according to the service block allocation. This allocation can be changed.
- Imaging resources
  Imaging devices such as MRI machines can be added, removed, or given a new schedule.

The way our system works is we first build the list of resources currently in the hospital using our data warehouse. Then we set up the rules for allocating the resources by working with the subject matter experts in the hospital. Finally, we use our historical data to validate these business process definitions and adjust as needed.

Once we have all of the resources and rules, we can create our model to "lock" these resources by assigning them to specific patient encounters and treatment plans. The system closely correlates a semaphore locking algorithm. Once the model is built, the user will be able to add or delete resources or to change the business rules defining which encounters can use the resources.

4.3 Treatment or Process Adjustment

We would like our solution to support adjusting specific treatment plans, clinical processes or operation processes, in addition to adjusting resources. For example, if we are implementing a stroke initiative that has been shown to reduce stroke length of stay by 10% at other hospitals, we can use our model to predict our measures given that all stroke patients need 10% less treatment time. If we have an initiative to write discharge orders or lab orders earlier in the day, we can analyze the potential effect of this change, and the appropriate alteration in staff schedules. If we have a program to reduce red blood cell transfusions by 50%, we can analyze the likely effect of this improvement on additional results such as length of stay, readmissions, hospital-acquired infection rate, cost, and lab productivity.

4.4 Use Case Examples

In this section we will list example use cases we have been given as potential questions this solution would be able to answer.

1. Volume changes. Do we have the capacity necessary to achieve the annual projections for growth by service line? Do we have the capacity necessary to handle the increase expected from expanded primary care coverage?
2. What-if scenarios:
   a. Asset reallocation including bed assignment, OR hours and staffing
   b. Process changes such as increased transfers to auxiliary hospitals or reduction in outpatient usage of beds
   c. Treatment changes such as reduced readmissions or performing triage in waiting rooms

d. Performance improvement such as reduced OR turnaround times

4.5 Goals

As we look at this vast number of potential measures, use cases and what-if scenarios, it is important we focus on the strategic goals. These goals are to optimally assign resources and create processes that increase volume and patient satisfaction while reducing cost, length of stay, readmissions and mortality.

5 IMPLEMENTATION PLAN

5.1 Phases

This project is broad so our goal is to create a model that can be expanded throughout several phases.

Phase 1: Proof of Concept
In this phase, we will create the model specific only to beds and surgeries. We will calculate the volume, throughput and utilization measures excluding staffing and block utilization. We will concentrate on a single use case: What will happen when we experience growth by service line according to projections?

Phase 2: Adjusting assets and treatment plans
In this phase we will build on phase 1 by allowing beds to be reassigned, operating rooms to be added and treatment plans to be changed. We will focus on the complex scenario: Predict the measures given that we reassign X number of beds from the surgical ICU to the medical ICU, we reduce surgical ICU length of stay 10% and we open one OR on Saturdays for non-emergent cases. This shows how scenarios need to include multiple factors to truly allow what-if analysis, and the ability of the model to support this.

Phase 3: Adjusting operating room schedules
Currently, some operating rooms are pre-assigned to specific services on specific days. This is a virtual floating OR and does not specify the physical room where the surgery takes place. In this phase, we will support what-if scenarios where the blocks are reassigned and we will include the block schedules in assigning OR rooms and staff to encounters. We will also add the measure of OR block utilization.

Phase 4: Anesthesia and ancillary staffing
In this phase, we will add measures around staff productivity, we will include staff capacity in our model and we will support what-if scenarios of changing staff levels specific for anesthesia, labs and images. We are not including nursing or attending physician staffing to reduce complexity. Nurses are generally staffed to bed occupancy anyway. To add staffing to our solution, we will bring in data from human resources and from the time and attendance tracking system.

Phase 5: Cost
In this phase we will add cost data to get an understanding of the financial impact of the what-if scenarios from the previous phases.

Future Work
In the future, we can see going beyond manual what-if scenario configuration to an optimization model where all possible changes are considered and optimal reassignments are proposed by our AI engine.

5.2 Team

The best opportunity for success in this project comes from building a diverse team of experts in different complimentary disciplines. Our team includes data warehouse architects, statisticians, academic experts, operational leaders, clinicians and user interface specialists. Our purpose in detailing the team breakup is to explain that we do not view this as simply a technology or IT project. The best opportunity for success is to create a project directed by the business which includes clinicians, researchers and academics, and technologists.

5.3 Technology

We have investigated using both commercial and open source digital twin products, but instead, our plan involves leveraging the technology the hospital already has invested in. This includes Microsoft SQL Server and an advanced enterprise data warehouse which will support both calculating the KPIs for the current environment and providing the historical patients and treatment plans needed for our model. This tight integration allows us to continue to support our enterprise data definitions and “single version of the truth” in both the actual data warehouse and the new virtual model. We also utilize Cisco DV, a data virtualization platform that allows us to quickly integrate multiple data sources and manage information independent of physical source. This is important as we bring in human resource data, cost information and time and attendance records. Cisco DV platform can also be used to enhance our system with auxiliary data such as avoidable delays or hospital-acquired infections from our epidemiology

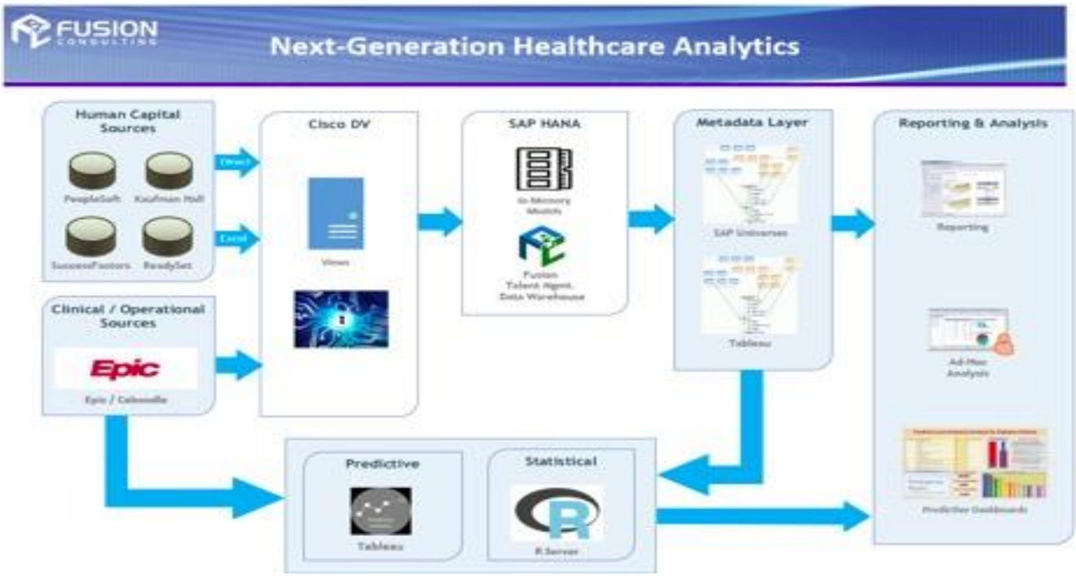

Figure 1: Data analytics system architecture.

system. Additionally, we are leveraging SAP HANA (Farber 2012), an in-memory data analytics appliance which will provide exceptional performance and has a built in predictive analytics library. We are also using R, an open source language specifically targeted to advanced statistics and predictive analytics. System R, originally a IBM product, is an open source suite of such tools and algorithms. "R has also been identified by the FDA as suitable for interpreting data from clinical research." (Smith 2012) Finally, we are using the dashboard visualization tool Tableau. Tableau is already in place at our hospital as the delivery mechanism for dashboards and data discovery, and it supports both HANA and R. This allows us to create a common set of tools, data definitions and interfaces rather than introducing new technology and learning curves.

Figure 1 shows our system architecture.

5.4 Specific Implementation Plan

In this section, we will detail our implementation tasks and plan for successful phased execution of this project.

5.4.1 Calculating the KPIs

For the first phase, we are targeting the KPIs around discharge, transfer and surgical volume, and around length of stay, census, bed utilization, isolation and boarding times. Most of these data points are in the enterprise data warehouse, but we need to aggregate them appropriately and add a few fields around the transfer center and isolation status. It is important that we have the current and historical state of these metrics calculated in a way that is accurate and uses matching patient cohorts. This allows us both to compare our what-if scenarios to current state, and, very importantly, to test our predictive model.

5.4.2 Data Preparation

We need to create our historical patient encounters. We do this as a multiple stage process. First, we extract from our data warehouse and build an event log for each hospital encounter. This log includes timing information concerning all patient movement. This will include arrival and triage time, each bed movement, each order which changes the patient's status or level of care, each level of care or service change, and the admit and discharge orders. Additionaly,l we add events surrounding surgeries: when they were scheduled, when they were performed, how long they took, etc.

We then use our statistical tools and biostatisticians expertise to convert our historical event logs to treatment plans. For example, consider a patient who spent 1 day in inpatient ICU status, but physically still in the ED and two days in ICU status in a ICU bed. Does their treatment require two days of ICU care or three? The answer is probably somewhere in between because they were receiving care while in boarder status in the ED, but not the same care as they would have received in the ICU. The goal of the statistics in this phase is to determine the relationship of boarder time to length of stay.

Once we have this information, we store with each historical encounter a mini treatment plan.

5.4.3 Modeling the Assets

For phase 1, the assets we care about are limited to just beds and operating rooms. For each bed outside of ED, we generate a bridge table which shows every class/service/level-of-care combination supported by that bed. We also map the beds to rooms (which is already in the data warehouse). Now we have a list of resources which we can use to support events on our encounters and mini treatment plan.

It is also interesting to note that our hospital has reassigned or added these bed resources in the past. We load this information as type-2 historical information using standard data warehousing methodology. This allows us to view our historical records in context and more accurately extract appropriate treatment plans. Also, because we have past change scenarios and actual results, we have real and meaningful data and situations available for us to validate our prediction model.

For ED, we have six types of beds: rapid intake, adult, express care, pediatric, diagnostic and surgery. ED is modelled somewhat differently. The only deciding factor are acuity, age, and time of day (express care is not open 24 hours a day).

For operating rooms, we load the list of operating rooms/locations, the prime time hours and the staffed hours for emergent cases. We are not concerned with service block schedules in the first two phases.

5.4.4 Building the Allocation Agent

We build a set of coded procedures which support the treatment plan of patient encounters by:

- Assigning the patient to an appropriate bed when they are in boarder or waiting room status
- Adding a hold to the other bed in a room (based on gender and isolation status)
- Moving patients around to support holds (for example if two males are in separate rooms with empty beds in a unit and a female needs a beds, the males can be moved together)
- Assigning an operating room based upon the schedule request and executing a surgery

5.4.5 Additional Statistics

We calculate additional statistics to support our model. These include:

- Histograms which tell us how many patients to expect at specific times
  This allows us to more accurately feed patients into our predictive model.
- Transfer center statistics to show us the relationship between the wait time for approval and the cancellation rate
  This will allow us to predict transfer volume and acceptance rate.
- ED statistics to show us the relationship between delays in treatment and patients leaving prematurely
  This will allow us to predict how many patients will leave prematurely based upon the predicted waiting times.
- Discharge processing statistics to show us the relationship between discharge order times and volume to actual discharge times.
  This will allow us to predict when a patient will actually be discharged in relationship to when the discharge order was written.

5.4.6 Virtual Model Execution

To execute our model, we place patients in the hospital (via ED arrival, direct admit or transfer request) according to our histograms from the statistical analysis. We then loop every “15 minutes” on our virtual clock and add new patients, discharge patients, and attempt to move patients according to their treatment plan. At any point in time, a patient is either in appropriate status or boarder status. For example if the treatment plan says the patient needs 3 days in ICU and they are currently assigned an ICU bed and have only been in ICU one day in our virtual system, they are appropriately placed and we will not attempt to move them during this time loop. If they are in intermediate level of care according to their treatment team, but they are in that same ICU bed, we will attempt to assign them an intermediate bed. If we are able to do so, we will release the ICU bed.

Each time a patient leaves the hospital in our virtual model, we record statistics about their encounter to match our KPIs.

The priority order we assign patients to beds is very important in our model execution. We will use business rules that define which types of patients it is most important to place first.

We load our patients completely randomly. We take a number between 0 and 1 and multiply it by our number of patient encounter treatment plans to choose one. To make up for this randomization, we run the same patients through with different random variations thousands of times to calculate the median KPI values and the histogram of each measure. This allows us to not only predict the measures but also show where the potential for challenges or logjams is. For example, it is possible that a given scenario reduces length of stay on average, but has a greater chance of increasing length of stay during stress situations (high volume fluctuations).

5.4.7 What if Scenarios

The scenario we are supporting for Phase 1 simply involves adjusting the patient encounters according to given growth projections by service line. We can achieve this with our statistics which define patient encounters to add to the virtual hospital model.

For phase 2, we support three types of adjustments: beds (add/delete/reallocate), operating rooms (add/delete/change hours) and treatment plan.

Our system will allow the user to set up a scenario. They can remove any bed in the system. They can add a bed and define the class/level of care/service combinations the new bed supports. They can also specify rules for adjusting patient treatment plans, such as reduce ICU length of stay for all sepsis patients by 10%.

5.4.8 Testing

Before we use our model to make decisions, it is obviously important to be certain our predictions are accurate. To achieve this our plan is to use a traditional training and testing process. We will train using historical data from encounters 6-24 months ago and then test by attempting to accurately predict the last 6 months for the hospital.

Additionally we will use past changes for testing purposes. Consider if 6 months ago our hospital added 5 beds to the adult medical ICU. We could train the system with encounters before 6 months ago, then set up a what-if scenario where these 5 beds are added. We use the predictive engine to predict the resulting volumes and length of stay, and test these predictions against our last 6 months of actual hospital statistics.

6 CONCLUSIONS

We have proposed a staged solution to allow hospitals to create “what-if scenarios” and predict system results from such scenarios over a large number of important measures. We have created an achievable, targeted plan which delivers value in each of several short phases as it builds the entire model. Our model leverages the EMR and enterprise data warehouse, well-known data mining techniques and bio-statistical algorithms. It uses biostatistics, discrete event simulation and business process modelling in tandem. It is achievable, measurable and flexible. We believe it will create a solid foundation for predictive analytics for our hospital system.

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