Predictive Analytics for better health and disease reduction

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Predictive analytics can be used effectively to evaluate enormous data generated by health care industry to extract useful information and establish relationships amongst the variables. In our country, health care providers have just began to hear of predictive analytics but are rapidly becoming aware that they have to make changes as the health care industry demands are changing.Unlike traditional statistical methods for data evaluation, Predictive Analytics uses artificial intelligence like statistical methods to reveal surprising associations which doctors would never even suspect.Hospitals, pharmaceutical companies and insurance providers will see changes from past treatment outcomes, latest medical research and databases like fewer complications, shorter hospital stay, fewer readmissions.

We have chosen a cardiac surgery Centre in New Delhi, where about 650-700 children with cardiac defects are operated every year, out of which about 1/3rd have tetralogy of fallot cardiac defect. Tetralogy of fallot is most common cyanotic congenital heart disease which comprise of VSD, aortic override, pulmonary stenosis, RVH.Firstly, we have selected important clinical features, i.e., Age, sex, Prematurity, Nutritional Status, Hemoglobin and Aristotle score which can affect post operative ICU stay. Secondly, we are using Data Mining techniques to evaluate the particulars of each patient.

Results: 450 patients underwent cardiac surgery for tetralogy of fallot from 2011 to 2013. Multiple linear Regression model identified age, male sex ($p<0.042$), malnutrition ($p<0.020$), prematurity ($p<0.028$) and higher hemoglobin (>21g/dl) ($p<0.035$) as independent factors predictive of increased ICU length of stay. When these five factors were analyzed in a regression model, the age ($p<0.001$) and Aristotle score ($p<0.001$) variable emerged as the strongest predictor of length of stay.

Conclusions: Although patient factors were influential, the age was the most important determinant of ICU length of stay after cardiac surgery. It may be possible to reduce length of ICU stay by identifying ideal age of patients to undergo cardiac surgery and encouraging surgeons to take sex, history of prematurity, hemoglobin levels in consideration before planning surgery for best outcomes.

Keywords: Cardiac surgery, Predictive analytics, ICU stay, Multiple linear Regression model, Associative classification.

1.Introduction

Predictive analytics involves the extraction of information from existing data sets so as to predict the outcomes and trends with an acceptable level of accuracy and reliability. Predictive analytics is a process that uses machine learning to analyze data and make predictions. It has been used for a long time, though the adoption has been low because of the complexity and costs.They can analyze current and historical data and facts to understand problems, identify risks and opportunities to come up with a number of solutions. It uses techniques such as data mining, machine learning and statistical modeling to help analysts. This business intelligence technology generates a predictive score for each element based on the training data and its learning experience.

Three levels of analytics, each with increasing functionality and value:
• **Descriptive**, standard types of reporting that describe current situations and problems
• **Predictive**, simulation and modeling techniques that identify trends and portend outcomes of actions taken
• **Prescriptive**, optimizing clinical, financial, and other outcomes
Much work is focusing now on predictive analytics, especially in clinical settings attempting to optimize health and financial outcomes.

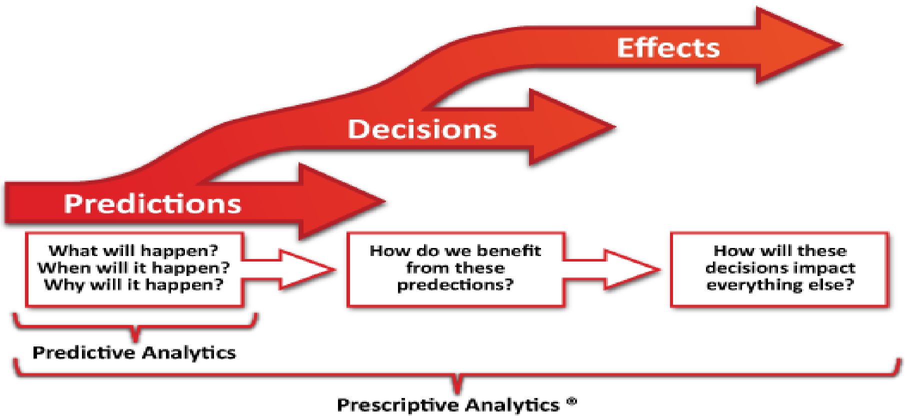

Fig: 1 Level of Predictive Analytics

Most healthcare systems are struggling to contain rising costs and allocate scarce resources effectively. Postoperative length of hospital stay is an important component of the overall cost of elective surgical services. Reductions in postoperative length of stay may produce cost savings that can be invested in other areas of surgical patient care. We decided to identify preoperative and intraoperative factors that predicted length of stay after cardiac surgery. By identifying these factors, we hoped to favorably influence future patient management.

With the digitization of clinical data, hospitals and other healthcare organizations are generating an increasing amount of data. In all healthcare organizations, clinical data takes a variety of forms, from structured (e.g., images, lab results, etc.) to unstructured (e.g., textual notes including clinical narratives, reports, and other types of documents). For example, it is estimated by Kaiser-Permanente that its current data store for its 9+ million members exceeds 30 petabytes of data.[1]Other organizations are planning for a data-intensive future. Another example is the American Society for Clinical Oncology (ASCO) that is developing its Cancer Learning Intelligence Network for Quality (CancerLinQ).[2] An analysis by SAS estimated that by 2018, there will be over 6400 organizations that will hire 100 or more analytics staff.[3]

Today lot of factors are driving health care transformation:

- Primary Care and Nursing shortages demand workforce productivity and efficiency
- New market entrants and new approaches to health and care delivery increase complexity and competition
- Growing costs for new, revolutionary technologies and treatments including shrinking reimbursements
- Increasing incidence and cost of chronic and re-emerging infectious diseases
- Health care is shifting from local to state and national contexts
- Changing demographics and lifestyles drive associated costs
- Empowered consumers expect better value, quality, and outcomes

A predictive model is in simple terms, a mathematical function that maps a set of input variables, usually in the form of records, and a response or output. The learning is supervised by presenting the model with a sample set of inputs and desired outputs till the machine comes up with a mapping structure. The machine learns the similarities, differences and patterns between the two sets and generates a mapping procedure. Consider the example of a predictive model that determines which of the customers is likely to churn. The input may include information like how much money is spent by the customer on merchandise and its frequency, his age and demographics etc. A customer saved is a customer earned. Much less expensive to keep or reactivate a customer than to find a new one.

The learning can be unsupervised in which case the machine itself figures out the output based on relations and similarity between the input data. The most common types are clustering models.

In *Supervised* this case the input includes all the features collected for each element along with the desired outcome. In *Unsupervised* the machine learns the similarities, differences and patters between the two sets and generates a mapping procedure. Consider the example of a predictive model that determines which of the customers is likely to churn. The input may include information like how much money is spent by the patients on their health problems and its frequency, his age and demographics etc.

Patient 1

- No complains in last 6 months
- 1 admission in hospital in 6 months
- Bill paid to hospital 60000 Rs
- Insurance premium paid 30000 Rs
- 54 years old male non smoker non alcoholic
- No Family history of heart failure

Patients

- 2 complaints filed against doctor
- 4 admissions in 6 months
- Bill paid to hospital 2.8 lacs Rs
- Insurance premium paid 30000 Rs
- 44 yr old male alcoholic and smoker
- Family history of heart failure

Fig. 2 Different patient profiles

2. Applications of predictive analytics

1.Fraud detection- A powerful data mining solution can shorten the inefficient and ineffective process of fraud detection and detect frauds earlier, with less labor and resources and a better accuracy rate.Insurers are also using predictive analytics to identify potential fraud mainly during the claims intake process. Fraud detection help decreasing number of auditors required and also increase chances of detecting frauds.

2.Marketing- Markets are under pressure to constantly increase their profits. With the help of predictive analysis, health care marketers can analyze customer data and turn them into actionable insights to increase their return on investment. Everyone is focused on cutting costs without decreasing business.Predictive analysis in general can answer, Who should be the targeted customers? What packages and services should be offered and how? How much should be the incentive? These models can be enhanced by combining the customer data with demographic and lifestyle data from third parties, although good models can be built without third party data. However access to it can enhance the accuracy and quality and reduce the time. Predictive modeling, in the area of direct marketing is called *response modeling using predictive analytics* using which we can target fewer customers and still get the same response.

3.Advertisement targeting- *S*calability, optimization and performance are the three most important factors in business technology. Predictive analytics can process huge, unstructured data sets in real time. With the recent increase in computing power, cloud-based analytics, and cheap data storage, the predictive tools can be used to study the interaction of advertising in media and sales channels. Exogenous variables are identified and how they affect ad performance. A prediction system is used to study the click / conversion rate of a campaign based on various attributes.

4.Insurance companies-Recent research indicates that nearly one-third of insurers are currently investing in predictive analytics and models. Insurers are constantly exploring new research areas and introducing new external data sources in order to gather additional information to better understand their areas. With the availability of a more robust database the opportunities to view risks from different perspectives increases and gaining insights that were not previously possible. Insurers are constantly using predictive analytics in the initial phases of the claims life cycle to decide on whether a claim deserves special attention. These flagged claims can then be assigned to a skilled claims adjuster, reducing losses and increasing resolution. Predictive analytics offer insurers the power to make the most of on the strengths of their resources and better control the cost during a loss. Insurance Data analytics revolves around predictive modeling using unstructured data such as insurance distribution, transaction and interaction data as well as social data.

5. Health Care- Although physicians are well trained, they can’t possibly retain the history of all the medical problems they have encountered and their solutions. Even if they have access to the huge amount of medical database, they would still require considerable amount of time to analyze the data and tailor it according to the patients profile. That is why more and more doctors are resorting to predictive analysis for health care.The “best evidence” approach is modeled on the framework of evidence-based medicine (EBM), applying the four basic steps of EBM to clinical data instead of scientific studies: [4]

• Ask an answerable question – can question be answered by the data we have?

• Find the best evidence – the best evidence is the EHR data needed to answer the question
•Critically appraise the evidence – does the data answer the question? Are there confounders?
• Apply it to the patient situation – can the data be applied to this setting?
Predictive analysis, go through the database to predict outcomes for the patient. The database could include data from previous medical cases and other journals and review papers. The predictions can range from responses to hospital readmission rates. Predictive Analytics uses techniques such as artificial intelligence and data mining to create a profile from past cases. The model is then used to provide a new individual patient with an instant prediction and an accurate diagnosis.

3. Advantages

Although Doctors are acute, well experienced and up to date with the latest research we can't possibly expect them to commit their memory to all the knowledge they need for every situation, and have it all at their fingertips. This kind of in-depth analysis is beyond the scope of a doctor's work.That's why more and more doctors as well as insurance companies are using predictive analytics. Predictive analytics uses techniques and statistical analytics to look through information and analyze it to guess outcomes for individual patients. Predictive Analytics not only helps uspredict, but it can also reveal surprising links in data that our human brains can’t identify.In medicine, predictions can range from predicting responses to medicines to readmission rates in hospitals. The statistical methods are also known as*learning models* due to their ability to grow in precision with the increase in number of cases. Predictive Analytics differs from traditional statistics (and from evidence-based medicine) in two major ways:**Firstly**, predictions are individualized and not made forgroups,**Second** Predictive Analytics does not follow a normal (bell-shaped) curve.Prediction modeling creates a prediction profile (algorithm) from past individuals using techniques such as artificial intelligence. The model is then "deployed" to provide instant prediction to a person for his needs, whatever it may be. For instance, the Affordable Care Act in USA, mandates that patients should not be readmitted before 30 days of being discharged from the hospital. Hospitals require predictive models to review when a patient can be discharged.

1. Predictive analytics increase the accuracy of diagnoses.

Doctors can use these predictive analytics results to improve instructional efforts tailored to individual patients. Doctors can have informed conversation with parents on their children’s postoperative progress and outcomes. Physicians and surgeons may find more joy in practice as positive outcomes increase and negative outcomes decrease. Consider a patient who comes to the ER, the doctors can decide to either send him home if there is no threat to his life or decide to admit him otherwise. If the doctors could answer queries about the patient’s condition to a system with anexperienced and precise predictive algorithm that would review the possibility that the patient can be sent home safely, then their clinical opinions would be supported. The prediction does not substitute their judgments but rather assists.The life of doctors will become less hectic as their role will change from decision makers to consultants. Also, hospitals will see less readmission rates and shorter patient stays[5].

2. Predictive analytics will help preventive medicine and public health.

Early predictions can help control the spread and severity of the disease and in the amelioration of the same. As population increases and lifestyles change, studying the patient may be a task every time. Predictive Analytics can help identify at risk patients and also help patients improve their lifestyle in order to avoid health problems. Predictive Analytics can easily incorporate the changes and provide results with sufficient accuracy.Predictive analytics, especially in the area of genomics, can allow doctors to recognize at-risk patients. With that information, patients can make changes to avoid risks and learn how to keep away from illnesses and learn about healthy practices. Genomics can play an important part, as in future medications might be individualized,as predictive analytics will be able to sort out what works for people with "similar subtypes and molecular pathways."

3. Predictive analytics provides physicians with answers they are seeking for individual patients.

Evidence-based medicine (EBM) has the ability to provide more aid than just hunches for physicians. However, it might be best suited for the people in the middle of a normal distribution but may not work for an individual treatment-seekingpatient.It is inefficient and risky to give treatments that are not desired or that won't work for an individual.Doctorscan use Predictive Analytics to decide the exact treatments for those patients. Improved diagnoses and better targeted treatments will obviously lead to increase in good outcomes and lesser resources used, together with the doctor's time.

4. Predictive analytics can provide employers and hospitals with predictions concerning insurance product costs.

Characteristics of workforce can be input into a predictive analytic algorithm to obtain predictions for medical costs. The data might come from the company's own database or from the data stored by their insurance providers. In association with insurance providers, Companies and hospitals, can synchronize their databases and actuarial tables to make models or techniques and health plans. Also, predictive models can be used to identify providers who will give the most effective products. As an example, metrics like "an average employee pays visit to a physician ten times a year" can be included in the model.Hospitals will also work with insurance providers as they seek to increase optimum outcomes and quality assurance for accreditation. In tailoring treatments that produce better outcomes, accreditation standards are both documented and increasingly met. When using Predictive Analytics, those organizations may see otherwise hidden opportunities for savings and increasing efficiency. Predictive Analytics has a way of bringing our attention to that which may not have been seen before.

5. Predictive analytics allow researchers to develop prediction models that do not require thousands of cases and that can become more accurate over time.

Initial models can be generated with smaller amounts of data and later improved with additional information numbers of cases thereby increasing the accuracy. The models are alive, adaptive and smart, have the ability to sense the changes in the environment. This fact stand very relevant in medical and surgical illness as data available is very limited.In medical, even small differences can prove significant to observational studies. Such studies are not feasible with traditional techniques. Predictive Analytics allows physicians to focus on the more important than the generic. For example, in an engineering journal it was mentioned that even small levels of alcohol could increase the threat of cancer in women. Following it women were warned to avoid alcohol.In the case of heart diseases, predictive analysis can be used to study the cases where young and healthy people suffer from heart attacks. In such cases the contributing factors vary widely and require special attention. The patients’ age, sex, blood pressure and blood sugar may be the input information.

The media,canlay their concentration on those small but significant findings to benefit the public. To benefit from the data from different practices, electronic database systems will need to be compatible, accountable, transparent, interoperability is very important. The risks of making mistakes are increased when dealing with human life, and the models used must learn to make the systemsuitable, sharable and dependable.

6. Pharmaceutical companies can use predictive analytics to best meet the needs of the public for medications.

Predictive Analytics can help finding individual choice of drugs for each patient. Incentivescan be given to pharmaceutical industry in order toproduce medicines for smaller requirements. As a result, Old medications, that were not used by a larger population,can be brought back due to theireconomic feasibility. For example, if 25,000 people need to be treated with a medication "shotgun-style" in order to save 10 people, then much waste has occurred as all medications have unwanted side effects.

7. Patients have the potential benefit of better outcomes due to predictive analytics.

There will be many benefits in lifestyle of patients as the use of predictive analytics rises. Patientwill be more informed and work in collaboration with their physicians to get better results. Predictive models, apps and medical devices and increased accuracy will help make patients become more aware of possible personal health risks sooner. They will then have decisions to make about their way of living and their future health.

8. Benefits of Predictive analytics for health care providers online:

Predictive search can analyze click-through activities, preferences, and history in real-time. The customer finds the front-end search interface easy. One can offer best promotions to the customer by Identifying promotions that have worked in the past, and then offer them in real-time based on the customer’s browsing pattern. Predictive analytics can analyze pricing trends in association with sales data to decide the prices that can maximize income and profit. A better understanding of patients leads to helping them improve their offering of the services they desire and at the price they requirealong with an effective post-admission service. Predictive analytic models can predict what a customer will like even if customer hasn’t vocalized his demands and needs.

4. Disadvantages

- Compatibility is needed for electronic data record systems to work together along with traceability, transparency and accountability.
- Even small inaccuracies may lead to irreparable damages and in this case the patients life may be at risk. The models in addition, also need to be valid, sharable and reliable.
- Even if the issues of interoperability, privacy, and processing of unstructured data are addressed there are still many factors influencing the health many of which are still difficult to be explained by medical science. The lack of an effective, closed feedback loop makes it a struggle for algorithms to continue to learn and improve. The greatest challenge is still the ability to produce action.

- It is still difficult to convince physicians and surgeons to follow the advice generated by Predictive Analytics.
- Some programs are proprietary, and require the users to pay for accessing the company's database.

5. Recent Predictive Analytics in Healthcare

Medical tourism is increasing rapidly in healthcare industry especially cardiac surgeries. May be a manager needs to decide which particular emerging countries offer the best target for their particular mix of products. Will Brazil be a better bet than China or Russia?Following questions are relevant in recent era like "What could you do if you could apply analytics across your entire data sphere with no constraints? What would you learn by connecting preoperative patient data, postoperative outcome, predictive analysis, customer's sentiments, and doctors input records? How could you improve inventory management by looking across patient outcomes, predictive analytics?"

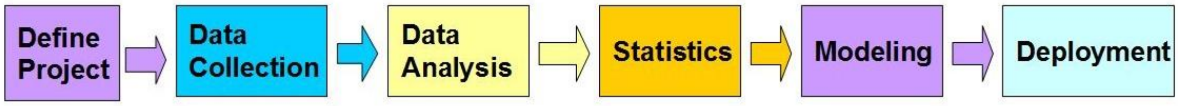

Fig 3: Predictive Analytics Process

For example, Predictive Analytics from both structured and unstructured data is imperative to early detection and prevention of heart failure and improving patient care at cheaper costs that was earlier proven to be difficult. The care model should be an effective way to reduce the standardized costs while providing personal level treatment to patients to produce the best possible outcomes.

While some heart patients may require long-term chronic disease management for issues like congestive heart failure others might require short high expense services like valve repair. Congenital heart defects are complicated heart anomalies, which need surgery at appropriate time, which is decided by type of defect and other preoperative factors. Predictive analytics can prove to be very useful to predict surgical outcome and decision making also. Postoperative care a patients socioeconomic data, their residence, ability to commute and sanitation can work to predict whether the patient will require follow up care or not. This requires predictive analytics to analyze large amounts of data and predict the outcome.In cases of heart care, where every second matters predictive analysis can suggest medications with a satisfactory level of accuracy and prove detrimental in saving a patient's life. In case of cardiovascular disease, by early prediction and identifying patients at high risk, preventive measures can be suggested such as to cut down trans fats, losing weight, and quitting smoking.

A patients medical history is an important factor in the decision making process of preventing chronic diseases.

1. Atlanta's Emory University Hospital a high profile medical center has partnered with IBM and Excel Medical Electronics for aSmart medical equipmentproject, which can record 1,000-2,000 data points for every patient visiting their center.
2. Doctors at Emory use a research grade analytics system to view real time visualizations of their patients heart beat rhythm to spot the heart disorder atrial fibrillation at

considerably early stages of the disease. The patients show no explicit symptoms but are often at high risk of heart failures.

3. The advisory board, a health care technology, consulting firm in partnership with major American hospitals in prevention of congestive heart failures and other conditions like diabetes and pneumonia.
4. Smart medical devices are being built that can digitize medical records and build network connection maps of all sorts of health care factors.[6]

Clearly a large and growing body of research demonstrates that EHR and other clinical data can be used to predict outcomes, including adverse ones, as well as diagnoses and eligibility for research studies. The next step in research is to find evidence that such methods lead to improved patient outcomes. Predictive analytics models

- Time series models- Models which predict based on time i.e. have time based predictions. For e.g. simple double and triple exponential smoothing.
- Regression algorithms- These models predict continuous variables based on other variables in the databases. e.g. logarithmetic exponential, linear and geometric regression models.
- Decision tree- Classify and predict discrete variables based on other variables of the database. E.g. CNR tree.
- Association models- These models analyze the dataset to find associations among data patterns. E.g. apriori
- Clustering models- These models cluster data that seem similar to analyze them better for similar characteristics. E.g. knn.
- Neural network- It does the forecasting, classification and statistical pattern recognition. E.g. MONMLP neural network.
- Ensemble models- Multiple predictions are done by varying the input conditions slightly every time.
- Naive Bayes- These apply Bayes algorithm with strong independent assumptions to come up with a highly probabilistic outcome.
- SVM- These are supervised learning methods that use associated learning models to analyze and recognize patterns used for classification and regression analysis.

There are unfortunately a small number of studies, and their results are mixed. One study showed that a readmission tool applied to an existing case management approach helped reduce readmissions.[7] while another found that use of a Bayesian network model embedded in EHR to predict hospital-acquired pressure ulcers led to a tenfold reduction in such ulcers as well as a reduction by one-third in intensive care unit length of stay for such patients.[8]

Another study found that a readmission risk tool intervention reduced risk of readmission for patients with congestive heart failure but not those with acute myocardial infarction or pneumonia.[9] Another study found that an automated prediction model integrated into an existing EHR was successful in identifying patients on admission who were at risk for readmission within 30 days of discharge, but its use had no effect on 30-day all-cause and 7-day unplanned readmission rates in the 12-month period after it was implemented.[10] A number of other critical clinical situations have been amenable to detection by analytics applied to EHR and other clinical data.

Predicting 30-day risk of readmission and death among HIV-infected inpatients [11] Identification of children with asthma [12] Risk-adjusting hospital mortality rates [13] Detecting postoperative complications [14] Measuring processes of care [15] Determining five-year life expectancy [16] Detecting potential delays in cancer diagnosis [17] Identifying patients with cirrhosis at high risk for readmission [18] Predicting out of intensive care unit cardiopulmonary arrest or death [19] Additional efforts have focused on helping to identify patients for participation in research protocols or improve diagnosis of disease: Identifying patients who might be eligible for participation in clinical studies [20] Determining eligibility for clinical trials [21] Identifying patients with diabetes and the earliest date of diagnosis [22] Predicting diagnosis in new patients [23]

6. Observation and Results

We retrospectively reviewed 450 patients who underwent cardiac surgery for tetralogy of Fallot congenital heart disease at a regional cardiac surgery center and teaching hospital, New Delhifrom 2011 to 2013. Data was collected preoperative factors (age, sex, prematurity, hemoglobin, nutrition, Aristotle score) that could potentially impact post operative length of stay.In our study, children from 1 month to 15 years were included. Children were classified as malnourished on basis of WHO classification using Z score. Children with Z score <-2 or more were classified as malnourished. Prematurity was defined as children who were born before 37 weeks of gestation period. As tetralogy of Fallot is a cyanotic congenital heart disease, hemoglobin levels are usually higher than normal individuals. We have taken hemoglobin level 21g/dl as cut off between two groups.The surgical unit studied is staffed by three full-time, and in our opinion equally competent, cardiac surgeons. Continuous data are presented as mean values with standard deviations (mean± SD). Multiple linear Regression was used to identify independent factors that may be predictive of ICU length of stay. In the multiple linear regression model a $p<0.05$ was considered significant. Statistical analysis was done using R language package software and technique statistical regression model.

Table 1 Summary data on 450 patients undergoing cardiac surgery for TOF

Age	6.5± 5 years
Sex (male:female)	240:210
Prematurity (yes:no)	128:322
Malnutrition (yes:no)	214:236
Hemoglobin level (<21g/dl:>21g/dl)	269:181

Table 2 Aristotle score

	Score	Level	Mortality	Morbidity	Difficulty
TOF repair, ventriculotomy, non transannular patch	7.5	2	2.5	2.0	3.0
TOF repair, no ventriculotomy	8.0	3	3.0	2.0	3.0
TOF repair, ventriculotomy, trans annular patch	8.0	3	3.0	2.0	3.0
TOF repair, RV-PA conduit	8.0	3	3.0	2.0	3.0
TOF repair, absent PV	9.3	3	3.0	3.0	3.3
TOF, AVSD repair	11.0	4	4.0	3.0	4.0

Table 3 Regression analysis of possible variables predictive of length of stay after cardiac surgery

Variable	Significance
Age	$p<0.001$
Sex	$p = 0.042$
Prematurity	$p = 0.028$
Malnutrition	$p = 0.020$
Hemoglobin	$p = 0.035$
Aristotle score	$p<0.001$

Results and discussion:

Pediatric cardiac surgery is a common operative procedures performed. In many centers, patients undergoing total correction for congenital heart disease (TOF) remain in ICU for approximately 3-4 days. These patients often have associated comorbid conditions that are responsible for prolonged hospital stay.450 patients underwent cardiac surgery for tetralogy of Fallotbetween 2011 to 2013. Data on these patients is presented in summary form in Table 1.Regression model identified age, male sex ($p<0.042$), malnutrition ($p<0.020$), prematurity ($p<0.028$) and higher hemoglobin (>21g/dl) ($p<0.035$) as independent factors predictive of increase ICU length of stay. When these five factors were analyzed in aMultiple linear regression model, the age ($p<0.001$) (Table 3) and Aristotle score ($p<0.001$) (Table 2)variable emerged as the strongest predictor of length of stay.

Our study was motivated by a desire to reduce the ICU length of stay after cardiac surgery. In this study, we have only examined preoperative and intraoperative factors that may influence length of stay. We have not considered postoperative factors, such as complications. By restricting our analysis to preoperative and intraoperative factors we remained focused on the question of interest, namely, what can we do preoperatively to predict and reduce length of stay?Preoperative selection of patients for cardiac surgery can be guided by age of the patient as patients with ideal age should be selected for surgery so that postoperative course is smooth and short. As trend is towards early correction of heart defects but according to our study shortest ICU stay was seen in children between 1-1.5 years of age. Post operative course can be expected to be prolonged in male patients, children who were born prematurely, malnourished, high hemoglobin level (>21g/dl) and higher Aristotle score. One of these factors, age, obviously cannot be altered but hemoglobin levels can be decreased by phlebotomy before surgery.

7. Conclusion

Predictive analytics serve Payors, Providers, Healthcare companies and patients. Decision of change in policy can be based on sound, objective information developed out of analytics.However, there is a continued need to improve the completeness and quality of data and conduct research to demonstrate how to best apply it to solve real-world problems.Hospitals faces the challenge of instituting changes that may lead to a shorter length of hospital stay after cardiac surgery. If ICU length of stay can be reduced consistently, we will have an opportunity to redirect valuable resources to other areas of cardiac surgical patient care. Data can be used by other hospitals to correlate and make better database, to monitor progress, identify needs and align resources, develop and evaluate intervention strategies, reallocate resources to address problems and deficiencies more effectively. Predictive Analytics can be used in how to avoid C-section, readmission rates, oncology patients prediction and plan management in advance, how to reduce hospital stay after appendicectomy and acute asthma attack. Return on investment reside in timely interpretation of that data followed by appropriate intervention. Changes are coming that can literally reform the way medicine is practiced for enhanced health and disease decline.

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References

1. Gardner E, The approach to Big data. Health Data Management, March 1,2013. www.healthdatamanagement.com/issues/21_3/The-HIT-Apprach-to-big-Data-Anayltics-45735-1(Accessed November30,2013).
2. Sledge GW, Miller RS, and Hauser R, Cancer and the future of cancer care,2013. ASCO Educational Book, 2013:430-434. Content 58-132.
3. Anonymous, An assessment of demand for labour and skills, 2012-2017, 2013, SAS: London, England. Big data Analytics_Report_Jan2013.pdf.
4. Hersh WR, Cimino JJ, Payne PR, Embi PJ, logan JR, Weiner MG, et al. recommendations for the use of operational electronic health record data in comparative effectiveness research, eGEMs (Generating Evidence & Methods to improve patient outcomes), 2013. 1: 14.vol1/iss1/14/. (Accessed December 1, 2013.
5. Maggie Van Dyke, mar 01, 2013: Predictive Analytics: Pinpointing How to Best Allocate Patient Resources. (www.hfma.org)
6. Neal Vngerleider, Big Data' www.fastcolabs.com/3035232/healthware/big-datas-next-challenges-heart-failure.
7. Gilbert P, Rutland MD, and Brockopp D. Redesinging the work of case management: testing a predictive model for readmission. American journal of Managed Care.2013,19:eS19-eSp25.issue, 2013, 11-vo;19-sp, redesigning-the work-of-case-management-testing-a-predictive-model-for-readmission. (Accessed December 4, 2013).
8. Cho I, Park I, Kim E, lee E, and Bates DW. Using EHR data to predict hospital-acquired pressure ulcers: A prospective study of a Bayesian Network model. International Journal of Medical informatics, 2013, 82:1059-1067.
9. Amarasingham R, Patel PC, Toto K, Nelson LL, Swanson TS, Moore BJ, et al. Allocating scarce resources in real-time to reduce heart failure readmissions: a prospective, controlled study. BMJ Quality & Safety, 2013. 22: 998-1005.
10. Baillie CA, VanZandbergen C, Tait G, Hanish A, Leas B, French B, et al. The readmission risk flag: Using the electronic health record to automatically identify patients at risk for 30-day readmission. Journal of Hospital Medicine, 2013. 8: 689-695.
11. Nijhawan AE, Clark C, Kaplan R, Moore B, Halm EA, and Amarasingham R. An electronic medical record-based model to predict 30-day risk of readmission and death among HIV-infected inpatients. Journal of Acquired Immunodeficiency Syndrome, 2012. 61: 349-358. Afzal Z, Engelkes M, Verhamme KM, Janssens HM, Sturkenboom MC, Kors JA, et al.

12. Automatic generation of case-detection algorithms to identify children with asthma from large electronic health record databases. Pharmacoepidemiology and Drug Safety, 2013. 22: 826-833. Escobar GJ, Gardner MN, Greene JD, Draper D, and Kipnis P.
13. Risk-adjusting hospital mortality using a comprehensive electronic record in an integrated health care delivery system. Medical Care, 2013. 51: 446-453.
14. FitzHenry F, Murff HJ, Matheny ME, Gentry N, Fielstein EM, Brown SH, et al. Exploring the frontier of electronic health record surveillance: the case of postoperative complications. Medical Care, 2013. 51: 509-516.
15. Tai-Seale M, Wilson CJ, Panattoni L, Kohli N, Stone A, Hung DY, et al. Leveraging electronic health records to develop measurements for processes of care. Medical Care, 2013: Epub ahead of print.
16. Mathias JS, Agrawal A, Feinglass J, Cooper AJ, Baker DW, and Choudhary A. Development of a 5year life expectancy index in older adults using predictive mining of electronic health record data. Journal of the American Medical Informatics Association, 2013. 20(e1): e118-e124.
17. Murphy DR, Laxmisan A, Reis BA, Thomas EJ, Esquivel A, Forjuoh SN, et al. Electronic health record-based triggers to detect potential delays in cancer diagnosis. BMJ Quality & Safety, 2013:Epub ahead of print.
18. Singal AG, Rahimi RS, Clark C, Ma Y, Cuthbert JA, Rockey DC, et al. An automated model using electronic medical record data identifies patients with cirrhosis at high risk for readmission.Clinical Gastroenterology and Hepatology, 2013. 11: 1335-1341.
19. Alvarez CA, Clark CA, Zhang S, Halm EA, Shannon JJ, Girod CE, et al. Predicting out of intensive care unit cardiopulmonary arrest or death using electronic medical record data. BMC Medical Informatics & Decision Making, 2013. 13: 28.1472-6947/13/28. (Accessed December 5, 2013).
20. Voorhees E and Hersh W. Overview of the TREC 2012 Medical Records Track. The Twenty-First Text REtrieval Conference Proceedings (TREC 2012). 2012. Gaithersburg, MD: www.trec.nist.gov/pubs/trec21/papers/MED12OVERVIEW.pdf.
21. Köpcke F, Lubgan D, Fietkau R, Scholler A, Nau C, Stürzl M, et al. Evaluating predictive modeling algorithms to assess patient eligibility for clinical trials from routine data. BMC Medical Informatics & Decision Making, 2013. 13:134. http://www.biomedcentral.com/1472-6947/13/134.
22. Gottlieb A, Stein GY, Ruppin E, Altman RB, and Sharan R. A method for inferring medical diagnoses from patient similarities.BMCMedicine,2013.11:194.1741-7015.
23. www.predictiveanalyticstoday.com/predictive-modeling/