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In this issue:

We're delighted to deliver Issue #4, with a strong focus on the intersection of Analytics and the teaching of Analytics. Our authors have studied Tableau as a supplement to Excel, LinkedIn Learning in Analytics courses, and Excel vs. Google Sheets. And our teaching tips and case studies include predictive analytics to predict acquittals at trial, and to predict the risk of falling in knee replacement patients, as well as a case using the timely topic of taxes.

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Information Systems Education Journal

Editors

Teaching Case

Health Care Management: Preventing Post-Surgical Falls after Hip or Knee Replacement Surgery through Predictive Analytics

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Abstract

The adult population in the United States is more physically active and are living longer than prior generations. Due to the advancement in surgical techniques and the increased number of active people, there has been a rise in the number of hip and knee replacement surgeries. This rise in the number of surgeries is expected to continue. Post-surgical care is a critical component to a successful patient recovery. After surgery, patients experience limited mobility while the muscles around the impacted joints need time for inflammation to subside. Physicians and other medical providers are concerned with making sure that patients do not experience falls during this time as it may lead to more serious injuries. A sample dataset of patients who underwent elective hip or knee surgery from January 2014 to March 2020 has been provided to analyze other medical conditions that may contribute to the likelihood of a patient falling. The goal is to identify important factors that can assist in predicting the probability of a patient falling after surgery.

Keywords: health care analytics, data science, predictive analytics, SAS Enterprise Miner™

1. CASE SUMMARY

Orthopedic surgeons are interested in understanding the factors that may increase the probability of a patient falling after hip or knee surgery. This is important for both patient health care and for medical cost control. A hospital from the northeastern United States has made over six years of patient data available. Personally identifiable data about specific patients is not included so at not to violate the patients' rights to privacy. The file contains data on the patients that underwent elective hip or knee surgery between January 2014 to March 2020. In this case study, current machine learning techniques will be used to identify factors that can contribute to a patient falling after surgery.

Based upon the data provided, post-operative falls after hip or knee surgery occurred in approximately 1% of patients. In statistical terms this is considered a rare event. A rare event occurs in a binary outcome when the probability of the outcome is low. This case provides an opportunity to use real life data to build multiple predictive models using a variety of tools (e.g., SAS, R, Python). It also provides an opportunity to work with rare event data.

2. BACKGROUND

Globally post operative falls and their subsequent injuries are a health care expenditure amongst the aging population. In 2014, patients over age 65 in the United States sustained 29 million falls, resulting in 7 million injuries, 800,000 hospitalizations, 27,000 deaths, and an estimated 31 billion dollars in annual Medicare expenditure (Bergen, Stevens & Burns, 2014). Recent literature suggests that patients who fall in the early post-operative period, after undergoing hip or knee replacement surgery, are more likely to experience a fracture.

Medicaid services, the single largest payor for hip or knee surgery in the United States, has identified in-hospital falls as a "preventable" acquired condition for which they would no longer cover in-hospital costs. Several studies have previously attempted to develop clinical tools to serve as predictors of inpatient falls (Conley, Schultz, & Selvin, 1999; Hendrich, Bender, & Nyhuis, 2003). Despite these interventions, post-operative joint replacement fall rates remain constant.

To better understand the factors that affect the likelihood of a patient falling, patient comorbidities, medications, and other factors will be analyzed. What is a *comorbidity*? When a patient has two or more health conditions at the same time, or if one condition occurs right after the other, this is considered a comorbidity. For example, a patient may have arthritis, a heart condition, and diabetes. Each of these would be considered a *comorbidity*.

The risk of falling increases significantly with age due to generalized osteoarthritis, tinnitus, cognitive impairment, and two or more comorbidities (Lastrucci, Lorini, Rinaldi, & Bonaccorsi, 2018). This risk is expected to continue to become a more prominent problem as the population continues to age worldwide. This is further compounded by the increase in implanted medical devices amongst younger patients due to hip or knee replacement surgery (Ong, Lau, Moore, & Heller, 2009). The most common types of falls observed from emergency departments (ED) are fractures (56%), superficial injuries (20.9%), and head injuries (8.7%), with the most common fractures being hip, wrist, and upper arm (Hartholt, van der Velde, Looman, van Lieshout, Panneman, van Beeck, Tischa, & van der Cammen, 2010).

Drugs, which are a modifiable risk factor have also been found to contribute to risk of falling. Benzodiazepines, which are commonly used to treat anxiety and sleeping disorders have been found to be associated with falls (de Jong, Van der Elst, & Hartholt, 2013).

There is great interest in determining which patients are likely at risk for falling and possible actions that can be taken to prevent falls. Hendrich (2013) developed and subsequently modified the Hendrich Fall Risk Model, (see Appendix A), as a simplified approach to try to determine patients at greatest risk for falls. The Hendrich Fall Risk Model is a scoring model that assigns points based upon known causes of post-surgical falls for the purpose of identifying which patients are most likely at risk. When using this scorecard approach, any patient with a score of 5 or higher is considered to be at higher risk of falling and therefore should have a higher degree of monitoring to reduce the likelihood of falling.

However, with the explosion of analytic technologies, there is a need to determine other causations to further reduce risk of injury and to further contain medical costs. A more sophisticated analysis is necessary.

3. DATA DESCRIPTION

The patient data set for analysis consists of data on 17,275 patients who have had hip or knee replacement surgery from a single hospital located in the northeast United States. Patients with incomplete data were not included. The available data set is comprised of three Excel files:

1. Patient file
2. Medications by Category
3. Comorbidity Description.

Patient File
The patient file contains basic patient characteristics and surgery data. Many of the patient demographic information has been omitted due to HIPAA regulations in the United States and to ensure that the patients are not personally identifiable. The data dictionary containing a list and description of the variables is provided in Appendix B. The file contains information about the patient such as their gender, body mass index (BMI), type of procedure (knee or hip), if the patient had a post-operative fall, if they were injured when they fell, and subsequent data related to the fall. In

addition, patient comorbidities for each of the patients is available. There are a variable number of comorbidities per patient. Some comorbidities are very common across the patient data set, for example, osteoarthritis. There are other comorbidities however, which occur less frequently.

The key number is used as a sequential unique identifier for each patient. Key number was used to uniquely identify each patient without personally identifying any individual.

Medications by Category File
Medications are an important consideration. The medications by category file contains information on the medications that patients were taking after their surgery. This includes medications directly related to the surgery as well as other medications that the patient was taking due to other, pre-existing comorbidities. After hip or knee replacement surgery, there are typically several medications that patients are prescribed, ranging from vitamins and muscle relaxers to opioids for pain management. The data dictionary is presented in Appendix C. The file contains one row of data per patient per medicine. Since most patients are using many different medications, the resulting file contains 190,699 observations (rows).

Comorbidity by Description File
The comorbidity by description file contains a list of comorbidity codes along with their accompanying comorbidity name. There are 3,797 different comorbidity codes. As a result of changes to medical coding over time, some descriptions may appear to be duplicates or very similar. These are included for completeness of understanding of comorbidity coding.

4. THE ANALYSIS

The goal of your analysis is to determine what factors affect the probability of a patient falling after surgery. This requires an in-depth analysis of the patients, their underlying comorbidities, and their medications to determine additional factors that may cause a patient to fall. Complete the following steps in your analysis.

Step 1. Prepare your data. The data sets were extracted from a patient medical record database. The format is not necessarily a final format for analysis, so consider how best to define a data set for analytic evaluation.

Step 2. Analyze and Transform Variables
Check the distribution of each of the variables. Based on these results do any of the variables need to be transformed? If so, please indicate which variables were transformed and which approach was used. Review the number of categories in your categorical data. Do any of these require additional grouping or binning? If so, consider how to bin the data in the context of how it would be useful to orthopedic surgeons, nurses, physical therapists, and other post-operative care givers.

Are there variables that should be rejected and would not impact the likelihood of a patient falling after surgery? How are missing values treated? This is a rare event analysis. How does that impact how the data is analyzed?

Step 3. Model Selection
Determine four or more appropriate modelling techniques to be used for analysis. What are the possible measurement criteria that could be used for analysis? What measurement will be used to evaluate the models? Why did you select this measure?

Step 4. Develop and Train Models
Check for multicollinearity and any redundancies. Appropriately partition the data for analysis and then check the model performance. What is the impact of a Type I or Type II error?

Step 5. Validate and Test the Models
Compare the results of each model. Which model performed the best. What could be done to further optimize the model?

5. FINAL REPORT

Prepare a final report that will help orthopedic surgeons understand what factors affect the probability of a patient experiencing a post-operative fall. Some of the variables will be obvious but what are some of the not so obvious variables that may impact the likelihood of a patient falling?

In your final report, be sure to discuss each of the five steps, any actions taken and the results.

6. REFERENCES

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APPENDIX A
Hendrich Fall Risk Model

Hendrich II Fall Risk Model		
RISK FACTOR	RISK POINTS	SCORE
Confusion/Disorientation/Impulsivity	4	
Symptomatic Depression	2	
Altered Elimination	1	
Dizziness/Vertigo	1	
Gender (Male)	1	
Any Administered Antiepileptics (anticonvulsants): **(Carbamazepine, Divalproex Sodium, Ethotoin, Ethosuximide, Felbamate, Fosphenytoin, Gabapentin,** Lamotrigine, Mephenytoin, Methsuximide, Phenobarbital, Phenytoin, Primidone, Topiramate, Trimethadi-one, Valproic Acid)[1]	2	
Any Administered Benzodiazepines:[2] (Alprazolam, Chloridiazepoxide, Clonazepam, Clorazepate Dipotassium, Diazepam, Flurazepam, Halazepam[3], Lorazepam, Midazolam, Oxazepam, Temazepam, Triazolam)	1	
Get-Up-and-Go Test: "Rising from a Chair" **If unable to assess, monitor for change in activity level, assess other risk factors, document both on patient chart with date and time.**		
Ability to rise in single movement - No loss of balance with steps	0	
Pushes up, successful in one attempt	1	
Multiple attempts but successful	3	
Unable to rise without assistance during test **If unable to assess, document this on the patient chart with the date and time.**	4	
(A score of 5 or greater = High Risk)	TOTAL SCORE	
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On-**going Medication Review Updates:**

1.**Levetiracetam (Keppra) was not assessed during the original research conducted to create the Hendrich Fall Risk Model. As an antieptileptic, levetiracetam does have a side effect of somnolence and dizziness which contributes to its fall risk and should be scored (effective June 2010).**

2.The study did not include the effect of benzodiazepine-**like drugs since they were not on the market at the time. However, due to their similarity in drug structure, mechanism of action and drug effects, they should also be scored (effective January 2010).**

3.**Halazepam was included in the study but is no longer available in the United States (effective June 2010).**

APPENDIX B
Patient File Data Dictionary

Variable	Definition
Key Number	A unique identifier for each patient
Gender	Gender of the patient; valid values are Female or Male
BMI	is a measure of body fat based on height and weight that applies to adult men and women
Patient Age at Surgery	Chronological age of the patient in years at the time of the surgery
Surgery Year	The year the surgery was performed
Primary Procedure Name	The type of surgery that was performed (i.e., hip or knee replacement)
Falls	An indicator to denote if the patient fell after surgery
Injury	An indicator to denote if the patient was injured because of a post-surgical fall
Location	Indicates where the fall took place (Internal is hospital, External is other than hospital)
90 Day Complication	Indicates if complications occurred within 90 days after the surgery
Subsequent Readmission	Indicates if the patient was readmitted to a hospital after the surgery
Subsequent_ED_Visit	Indicates if the patient had a subsequent visit to an emergency department after the surgery
Comorbidity Code	A unique code that defines a specific condition that impacts a patient

APPENDIX C
Medicine by Category

Variable	Definition
Key Number	A unique identifier for each patient
Medication Name	Name of the medication
Dose	Amount of medication administered
Route	Indicates how the medication was administered
Category	Group that the medication name belongs within