Constructing Patient-Data Warehouse to Understand Traumatic Brain Injuries and their Dynamics of Change

ALY6080: Experiential Learning

Final Project

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Executive Summary

Traumatic brain injury (TBI) is a highly complex and heterogeneous disorder of the central nervous system (CNS), which is rapidly emerging as one of the leading causes of death and disability worldwide. TBI can be caused by various types of physical forces and leads to a wide range of structural, physiological, behavioral, and molecular responses. Unfortunately, our understanding of the pathobiology of TBI remains limited, and there are currently no accurate diagnostics or prognostics available. Furthermore, the lack of specific therapies for TBI is reflected in the 100% failure rate of clinical trials. The current approach of analyzing small, curated datasets is insufficient to tackle the complexity of this condition.

Our project examines the distinct variations in symptoms of Traumatic Brain Injuries (TBIs) based on demographic factors and developing a database to facilitate access to data records for key attributes. To understand the condition better along, a dashboard is created for visualizing the outcomes of the treatments being provided to the patients. For data cleansing and database management, SQLite is our choice. To visually represent the analyzed data and create interactive dashboards, Tableau is chosen. R programming can provide a rich set of libraries and packages that facilitate descriptive analysis and predictive modeling. By leveraging these statistical tools, we endeavor to effectively analyze TBI data, identify patterns and trends, and present their findings in a visually compelling and easily understandable manner.
The goal is to extract valuable insights from the complex dataset and inform decision-making processes related to TBI symptoms and patient demographics.

Big Data (BD) offers a promising solution for addressing the challenges posed by TBI. With its capacity to collect, store, and analyze vast amounts of data, BD can handle unstructured, incomplete, and messy datasets that are characteristic of TBI. By leveraging artificial intelligence, machine learning, and cognitive computing, BD approaches can uncover novel correlations that traditional methods might overlook Thus, the first end-user of our project results will be the sponsor company. They can use ML models on this database to predict the dynamics of change in TBI therapies and triggers. Next, this database can be used by the patients, caregivers, and providers as a record of TBI incidents and symptoms. Ultimately, our project scope is attuned to giving better outcomes to end users over time, as the data gets updated with more records.

The main elements of this project are:
1) Data warehouse with all the reported data provided by the sponsors.
2) Tableau Dashboards giving an exploratory insight into the reported data warehouse.
3) 2 Predictive models including:
   a) A Decision Tree model to predict the feature importance and the trajectory of variables.
   b) A Random Forest model to further increase the accuracy and prediction of decision trees.

The statistical tools that can be useful to answer the above questions are:

1. SQLite for data cleaning and database management
2. R programming for descriptive analysis and predictive modeling
3. Tableau and/or Power BI for Visualizations and dashboards

The literature review and the project strategy so far pave the way for a methodical workflow, coordinated teamwork, and a solid chance at building meaningful models for our sponsors.

Literature Review

I. Traumatic brain injury (TBI) is a highly complex and heterogeneous disorder of the central nervous system (CNS), which is rapidly emerging as one of the leading causes of death and disability worldwide. TBI can be caused by various types of physical forces and leads to a wide range of structural, physiological, behavioral, and molecular responses. Unfortunately, our understanding of the pathobiology of TBI remains limited, and there are currently no accurate diagnostics or prognostics available. Furthermore, the lack of specific therapies for TBI is reflected in the 100% failure rate of clinical trials. The current approach of analyzing small, curated datasets is insufficient to tackle the complexity of this condition. Big Data (BD) offers a promising solution for addressing the challenges posed by TBI. With its capacity to collect, store, and analyze vast amounts of data, BD can handle unstructured, incomplete, and messy datasets that are characteristic of TBI. By leveraging artificial intelligence, machine learning, and cognitive computing, BD approaches can uncover novel correlations that traditional methods might overlook. The successful application of BD in domains such as logistics, counter-terrorism efforts, and healthcare demonstrate its potential. In the context of TBI, BD analytics can reveal intricate connections between physical forces, biological responses, functional impairments, and molecular pathologies, establishing causal relationships over time. To fully harness the power of BD, it is crucial to collect, store, and make all relevant data available for (re)analysis, thereby reducing the prevalence of "dark data." Customizing existing successful BD analytics approaches could provide an important proof of concept by establishing correlations between experimental and clinical data.

II. Flexible machine learning (ML) algorithms do not outperform traditional regression models when predicting outcomes after moderate or severe traumatic brain injury (TBI) in low-dimensional settings. This is because the main prognostic effects are independent and linear. A model's predictive performance is influenced more by the population to which the model is applied than by the specific algorithm used. This result highlights the importance of continuously validating and updating predictive models to ensure applicability to new populations, whether they are based on ML algorithms or regression models. doing. To improve the prognosis of traumatic brain injury, future studies should incorporate novel predictors such as biomarkers, imaging, and genomics that add significant value in identifying patients with poor or good prognoses., the current prognostic model should be extended. Comparing flexible ML algorithms and traditional regression models in a low-dimensional environment for predicting outcomes after moderate or severe traumatic brain injury yields interesting insights. The lack of performance superiority of flexible ML algorithms suggests that the most important prognostic factors in traumatic brain injury independently and linearly influence. Furthermore, this study highlights that the applicability of predictive models depends on the specific population studied rather than the choice of algorithm. This highlights the need to continuously validate and update predictive models to ensure their effectiveness in different populations. To advance the prognosis of traumatic brain injury, future research should focus on extending current prognostic models by integrating new predictors such as biomarkers, imaging, and genomics. These additional factors may significantly improve the identification of patients with good or poor prognoses, thereby improving clinical decision-making in traumatic brain injury cases.

III. Traumatic brain injury has become an urgent problem for the elderly and poses a significant socioeconomic burden to society, but as the population ages, the incidence of traumatic brain injury in the elderly is expected to increase. , has become a serious problem in both medical and traumatic brain injury. Not only treatment but also socioeconomic impact. Given the severity of this problem, it is essential to prioritize the development and implementation of effective strategies to reduce the number of older people with traumatic brain injury. Reduce the incidence of invisible falls, the leading cause of TBI in this population, by focusing on preventive measures and raising awareness of TBI risk factors and their effects in older adults. can be reduced. These proactive measures will not only improve the well-being and safety of the elderly but also have significant indirect benefits, such as reduced health care costs in Singapore and reduced socio-economic burden associated with traumatic brain injury. A better understanding of the outcomes and prognosis associated with this condition is critical to addressing the challenges that traumatic brain injury poses to the elderly. Prospective data collection can play an important role in this regard by providing valuable insight into the factors that influence the course and outcome of traumatic brain injury in older adults. The systematic collection of data from a patient's first visit to the emergency department makes it possible to develop a standardized outcome assessment specifically tailored for traumatic brain injury cases in this population. This assessment will enable medical professionals to accurately assess the severity and prognosis of traumatic brain injury in elderly patients, enabling timely and appropriate intervention. In addition, standardized outcome assessments provide a comprehensive database that allows researchers and policymakers to analyze the long-term effects of traumatic brain injury in older adults and identify effective strategies for prevention and management. Helps build. Ultimately, these efforts will contribute to better health planning, improved patient outcomes, and reduced socioeconomic burden associated with traumatic brain injury among older Singaporeans.

Business Problem

Problem: The researchers in traumatic brain injury should strongly consider gender difference and age differences and explore the same in detail. A nuanced approach should be taken while considering female patients with TBI over male patients.

Background: Traumatic brain injury (TBI) is a major public health problem and while both genders are affected, very little is known about the difference between female TBI and male TBI. The present-day studies are constantly exploring epidemiological, clinical, imaging, and death aspects of female TBI, and how it differs from males. While the female TBI group constitutes a smaller proportion of TBI patients, they differ significantly in the severity of injury and mortality, when age is taken into consideration as well.

Relevance: In the literature, the characteristics, or differences unique to female TBI patients have not been explored in detail. Age and Gender are two aspects that can have a game-changing influence on the way treatments are provided to patients.

Objectives: The project aims at analyzing the key differences in symptoms of TBIs based on key demographics, creating a Database to provide access to data records for key attributes, and establishing models for predictive analysis.
To improve operations, we:

- Need to understand if there is any correlation between TBI symptoms and patient demographics such as age, gender, or medical history.
- Need to gain valuable insights to enhance treatment strategies and improve patient outcomes based on demographics.

The key questions that we plan to answer by the end of this project are:

1. How are TBI incidents different for males and females?
2. How do TBI symptoms unfold?
3. How to create a dashboard using Tableau that allows access to information instantly as per the requirement of a clinical researcher or therapy provider?
4. What are the relevant descriptive statistics that have the potential to make important revelations about TBI and related conditions?
5. What are the most prevalent therapies provided to patients?
6. Which symptoms are most common among TBI patients?
7. How can we create visualizations using Tableau to make certain facts about TBIs apparent?
8. How can we structure the data using MySQL to create a database for all the patient symptoms and treatment information?
9. How can we ensure we remove personal biases while cleaning the data records and interpreting the survey entries?
10. What kind of predictive models are best suited for this combined dataset?

Data Warehousing

The sponsor data consisted of a total of 30 data files and 8 reference files, all of which were in CSV format. These files contained a combination of structured, unstructured, and narrative data. To create a data warehouse, the first step was to design a table schema that included the necessary referential constraints such as primary keys, foreign keys, and not null constraints. This schema provided the framework for organizing and storing the data effectively.

Once the table schema was established, the next step involved importing the data from the CSV files into the corresponding tables in an SQLite DB browser. This process ensured that the data from the sponsor's files were readily accessible and could be queried efficiently within the data warehouse.

Data Cleaning

It's important to note that the data provided to us was collected from an application called Sallie. This app was utilized by patients, caregivers, and providers, and it offered predefined options for various variables such as patient_type, user_type, injury_from, head_hit_location, symptoms, and therapies. These default options served as a convenient selection for users, but the app also allowed individuals to choose "others" and provide additional details when the default options didn't accurately describe their condition. Consequently, these variables contained more than 30 unique values.

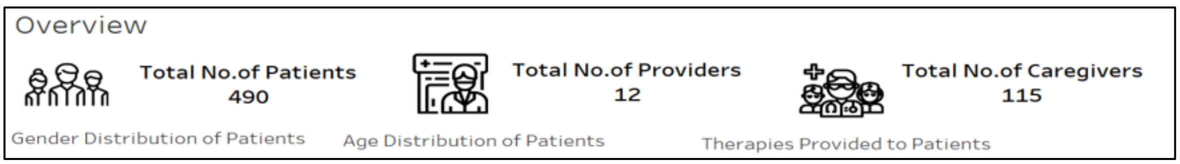
During the investigation and analysis of the data, it became apparent that the information given by users could be grouped into fewer categories. Although the data initially appeared to have numerous distinct values, closer examination revealed that many users were essentially describing the same thing using different words or phrases. Therefore, by utilizing the reference tables as a master data source, the values of the variables in the data tables were consolidated into a smaller set of distinct categories.

This process of grouping the data into more generalized categories enhanced the efficiency and effectiveness of data analysis. It allowed for a clearer understanding of the overall patterns and trends present in the data while reducing redundancy and improving the organization of the information.

Exploratory Analysis

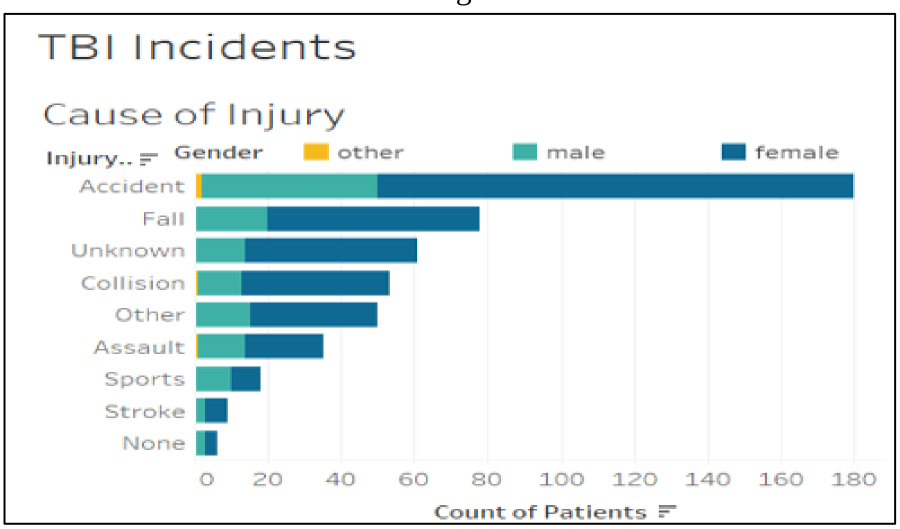
The exploratory data analysis for data on TBI patients is done through interactive dashboards and meaningful visualizations, to build a story for our stakeholders in a coherent fashion.

To get an overview of the number of responses recorded from Patients, Providers, and caregivers, we get the following tabs that show us that maximum responses have been recorded directly from the patients. This proves the authenticity of the dataset and makes the recorded information reliable for analysis.



Traumatic Brain injuries are caused due to many reasons. These are mostly externally induced and can lead to life-long conditions. It makes it crucial to understand which incidents have the highest potential to cause an injury such as this one, for various genders.

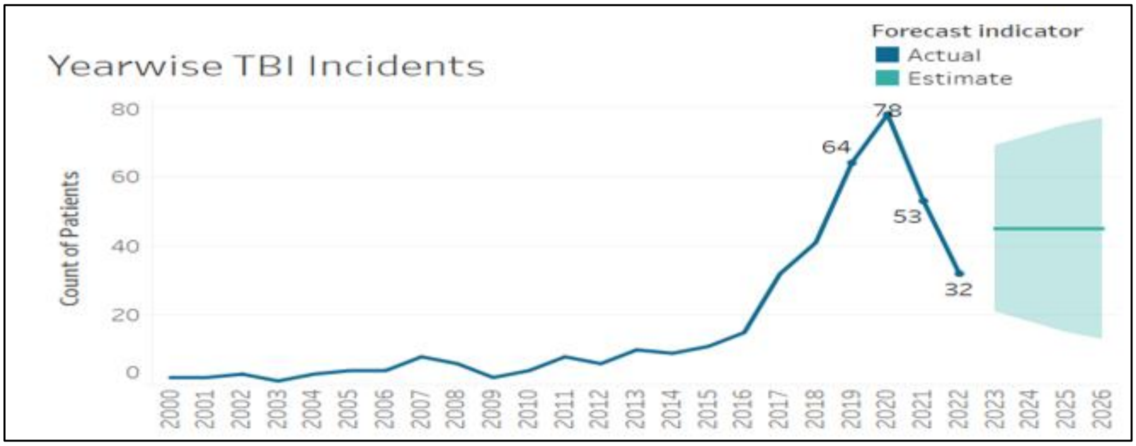
Figure 1: Most common TBI incidents based on genders:



The figure shows that accident is the leading cause of TBIs among both genders, followed by Collision and Assault. Sports is a bigger cause of TBIs in males than females, possibly because of less involvement of females here.

The dataset contains records of TBI patients starting from 2000 to 2023. Based on this timeline, we can see the year-wise growth in TBI patients up to 2023 and extrapolate this information to forecast the trend in the growth of TBI patients beyond the current year.

Figure 2: Time series Analysis of TBI patients till 2023 and beyond:



The actual growth in the number of patients recorded for clinical trials can be observed from 2016 onwards, reaching its peak in 2020. The possible cause of fall in response-recording since 2020 could be due to COVID outbreak. This could have led to a shortage of staff or simply lack of contact with the patients. A TBI-induced condition is complex and engaging with its patients requires trained staff and direct contact with the patient. Virtual engagement is often difficult and does not guarantee quality data.

Next step is to dig a little deeper into the gender and age distribution of the patients that are a part of this project. The following donut charts give us a clear picture.

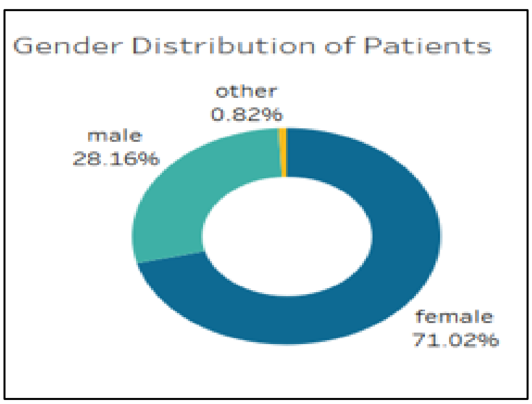


Figure 3: Donut chart for Gender Distribution

The gender distribution shows that over 71% of the TBI patients are females. This shows that TBIs are more common among females assuming that the sample is unbiased.

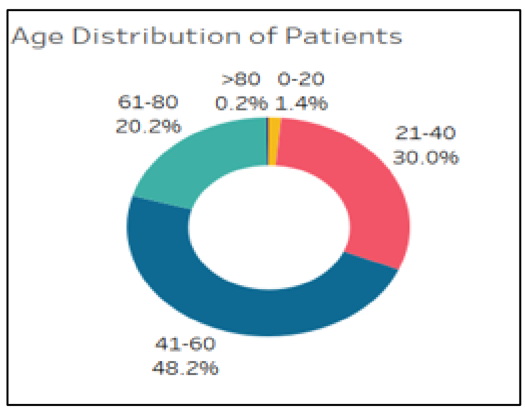


Figure 4: Donut chart for Age Distribution

Individuals in the age group of 41-60 years comprise of almost 50% of the TBI patients. This is followed by 30% of patients from 21-40 years. Thus, TBIs are more prevalent after 21 years of age.

Now, we move on further to analyze the dynamics of therapy provision and symptom experience among TBI patients.

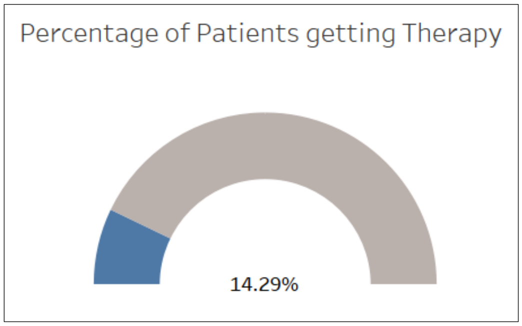


Figure 5: Proportion of recorded patients getting therapy for TBI:

Only about 14% of the recorded patients are receiving some kind of therapy for their TBI-induced conditions.

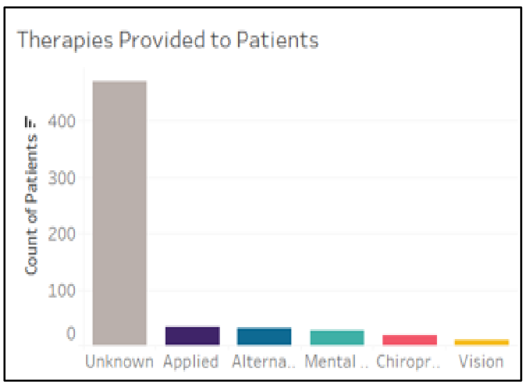


Figure 4: Bar chart for Therapies

While most therapies given to the patients are unknown in records, out of the ones that are known, the most common practice has been to extend Applied, Alternative and Mental therapies.

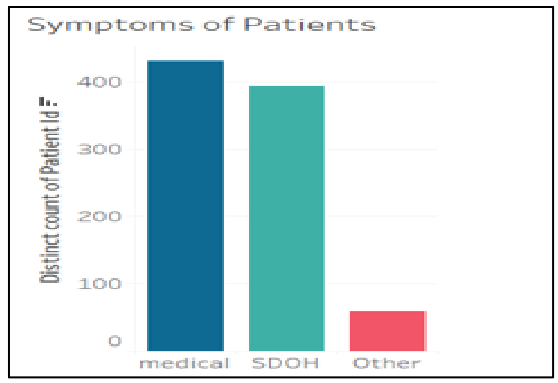
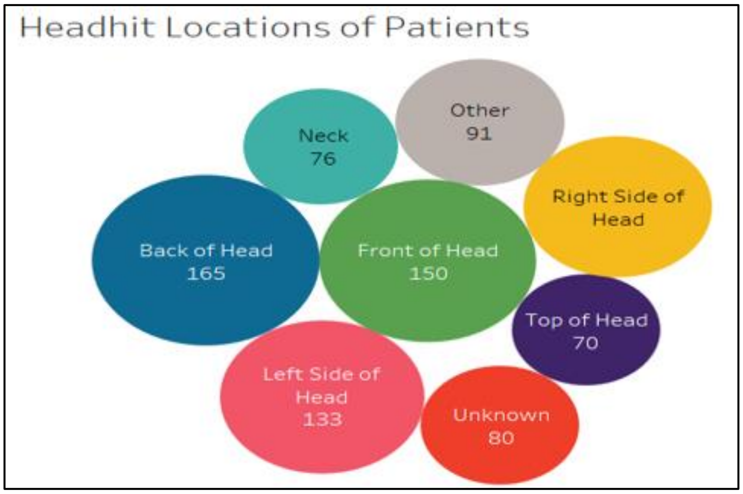


Figure 5: Bar chart for Symptoms

Majority of the patients are experiencing Medical, followed by SDOH symptoms. Thus, the focus of therapies provided can be directed in the medically.

We know that TBIs are usually caused due to accidents. These incidents require a direct effect on the head or neck. However, which location of the head is most vulnerable to a TBI requires a further analysis based on patient responses.

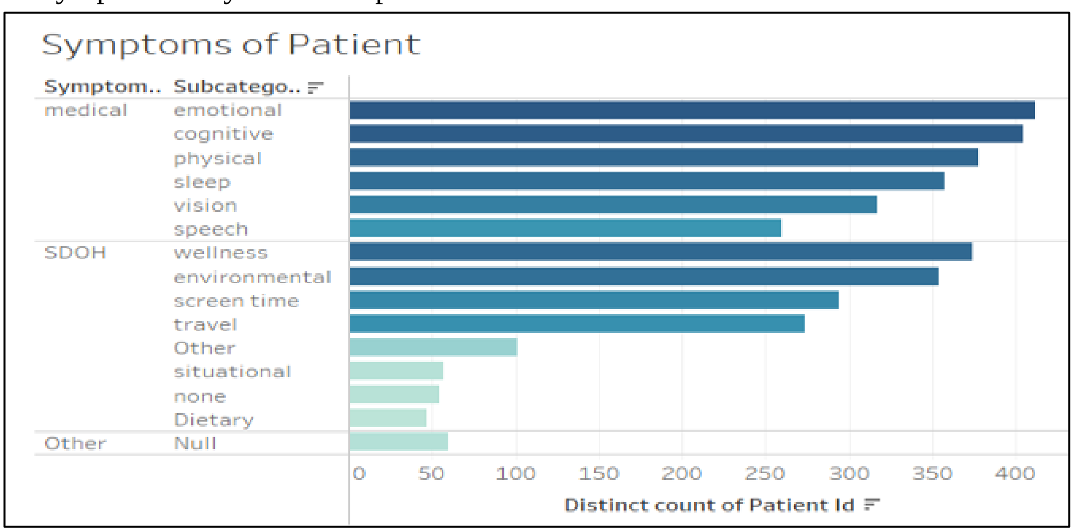
Figure 7: Head Hit locations of TBI patients:



The above Bubble chart shows that the majority of TBIs are caused due to hitting on the Backside, Front side, and Left side of the head of an individual when involved in a traumatic incident. The topside of the head is probably the least vulnerable part of the head of an individual.

TBI symptoms are spread over a range of categories within the Medical and SDOH group of symptoms. An in-depth symptom analysis is warranted to get some insights into the situation of a TBI patient.

Figure 8: Symptom analysis of TBI patients



While most patients experience medical symptoms, the subcategories within this group that are most prevalent are emotional vulnerabilities, Cognitive difficulties, Physical conditions, and sleep apnea. Among SDOH symptoms, the ones that require more focus would be wellness, environmental, and screen-time-related symptoms.

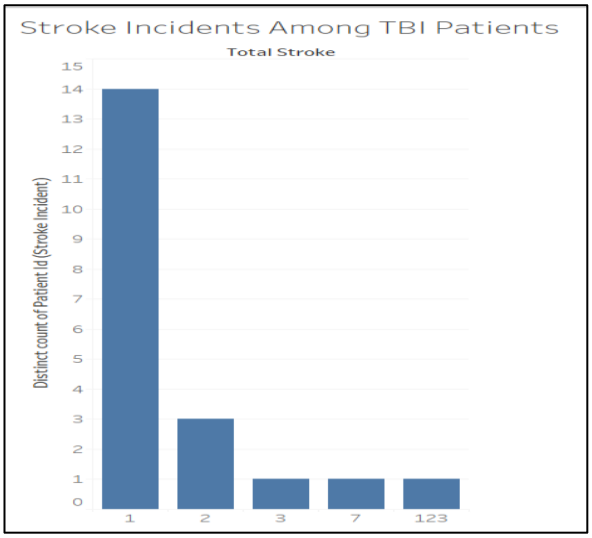


Figure 9: Count of patients with respect to number of strokes:

Out of all the TBI patients who got a stroke because of their condition, the maximum number of patients got a single stroke only. 3 patients got 2 strokes and there is a single record for patients getting 3 or more strokes.
The record showing 123 strokes on a patient is evidence of wrong entry by the surveyor. Such errors can be processed moving forward.

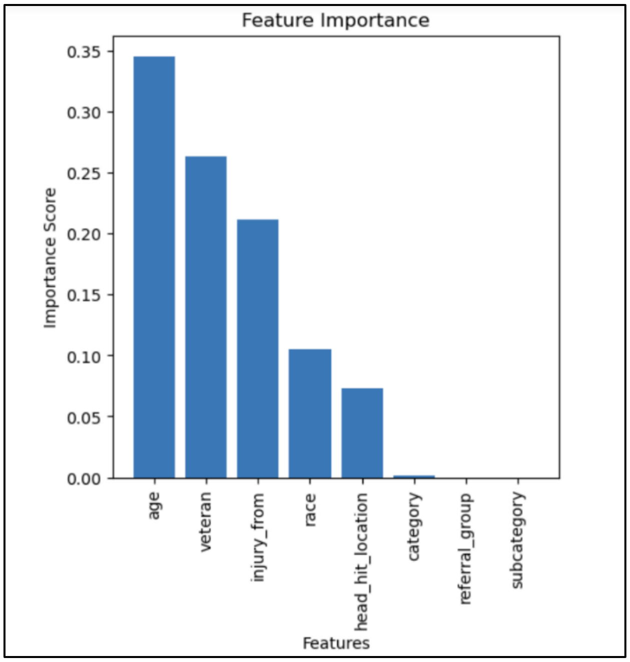
Data Modelling

A dataset for the model was created using a JOIN query that pulled different variables from different tables of the database. The dataset was then imported into an R data frame. Data is then divided into training and test sets based on the dependent variable gender. The model will first be trained on the training data set that contains 70% of the observations. Afterward, we will test the model using the test set containing the remaining 30% of the observations. Since the response variable in our dataset is categorical, we have chosen to develop two classification models: Decision Tree, and Random Forest models.

Decision Tree Model

The goal of using a Decision Tree is to create a training model that can be used to predict the class of our target variable 'Gender' by learning simple decision rules inferred from existing training data. This Decision Tree model is built with **'Gender'** as the response variable. The outcome is binary, that is, "male" or "female" and all the other variables are considered as the possible predictors.

Model Output: The features that are considered most important in predicting the gender of a TBI patient are Age, Race, head-hit location, and Sleep subcategory. However, irrespective of the patient's race, if the head location is front or back and the patient is less than 68 years of age, then the chances of the model predicting it as a female is very high, with an 11% chance of misclassification.



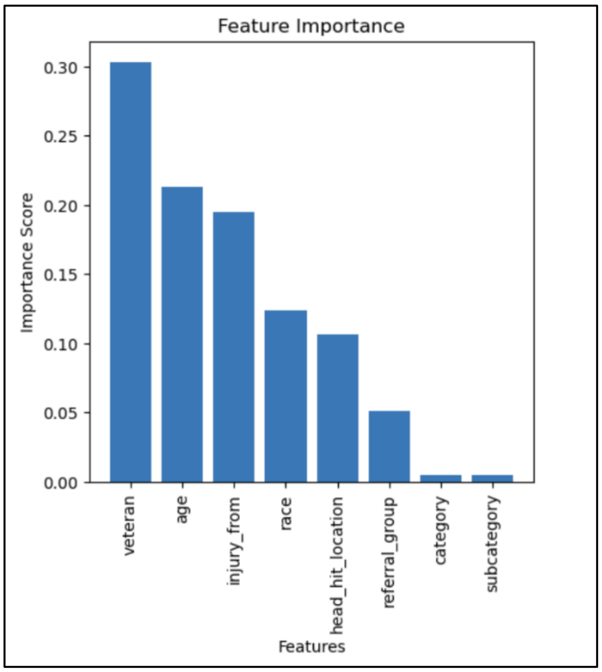
Model Performance: The Decision Tree model achieved an accuracy of 87.41% in predicting the target variable. The 95% confidence interval for accuracy ranged from 0.8589 to 0.8882, indicating a high level of certainty. Sensitivity was high at 94.66%, indicating that the model correctly identified most positive cases (female). However, specificity was lower at 68.27%, suggesting some difficulty in identifying negative cases. The positive predictive value was 88.73%, meaning that around 88.73% of the predicted female cases were accurate. The model demonstrated a balanced accuracy of 81.47%, indicating a reasonably good overall performance. In conclusion, the Decision Tree model showed promising results in predicting the female class, with high sensitivity and moderate overall accuracy.

```
               Accuracy : 0.8741
                 95% CI : (0.8589, 0.8882)
    No Information Rate : 0.7251
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.6658

 Mcnemar's Test P-Value : 9.773e-10

            Sensitivity : 0.9466
            Specificity : 0.6827
         Pos Pred Value : 0.8873
         Neg Pred Value : 0.8290
             Prevalence : 0.7251
         Detection Rate : 0.6864
   Detection Prevalence : 0.7736
      Balanced Accuracy : 0.8147

       'Positive' Class : female
```

Random Forest Model

This classification model creates multiple decision trees, and each tree will have a prediction. The most frequent prediction will be the final prediction of the model.

Model Output: The features deemed important in predicting the gender of the patient are Age, cause of injury, Race, and the location of head where it was hit during the injury. The age factor is important to predict females only till 69.5 years of age as per the final decision tree of the random forest model.



Model Performance: The random forest model achieved an accuracy of 91.28% in predicting the target variable. Sensitivity was high at 98.85%, correctly identifying most positive cases (female). However, specificity was lower at 71.30%, indicating some difficulty in identifying negative cases. The positive predictive value was 90.09%, meaning that around 90.09% of predicted female cases were accurate. The model showed good overall performance with a balanced accuracy of 85.08%. In conclusion, the random forest model showed promising results in predicting the female class, with high sensitivity and reasonable accuracy across the dataset.

```
               Accuracy : 0.9128
                 95% CI : (0.8997, 0.9247)
    No Information Rate : 0.7251
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.7623

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9885
            Specificity : 0.7130
         Pos Pred Value : 0.9009
         Neg Pred Value : 0.9592
             Prevalence : 0.7251
         Detection Rate : 0.7168
   Detection Prevalence : 0.7957
      Balanced Accuracy : 0.8508

       'Positive' Class : female
```

In conclusion, both models showed promising results in predicting the female class, with the Random Forest model performing slightly better in terms of overall accuracy.

Model Comparison

Metrics	Accuracy	Sensitivity	Specificity	Precision
Decision Tree Model	87.41%	94.66%	68.27%	88.73%
Random Forest Model	91.28%	98.85%	71.30%	90.09%

Recommendations & Findings

- **Gender Focus:** Since the majority of TBI patients in the dataset are females, it may be beneficial to focus on understanding the specific needs and challenges faced by female TBI patients. This can help in tailoring therapies and support systems to address their unique requirements. The two models have been instrumental in this direction by allowing us to find the most important features in predicting the gender of the patient.
  Since age, race, cause of injury, and head-hit location are the most important factors to predict the 'female' class of TBI patients, we can dig a little deeper into these to find how the symptoms and vulnerabilities of TBIs can unfold for both genders.

- **Age Group Focus:** Given that the age group of 41-60 years comprises almost 50% of TBI patients, it would be valuable to concentrate efforts on understanding the specific issues faced by individuals in this age range. Additionally, considering that TBIs are more prevalent after 21 years of age, it would be beneficial to focus on preventive measures and awareness campaigns targeted toward young adults.
  The models predict that if the age group of a TBI patient is less than or equal to 68 years, then age can be considered an important factor in predicting the gender of the TBI patient to be that of a 'female'.

- **Therapy Recommendations:** The analysis suggests that applied, alternative, and mental therapies are the most common practices among known therapies. It would be helpful to further explore the effectiveness of these therapies and consider integrating them into treatment plans for TBI patients. Additionally, since medical symptoms are the most prevalent, therapies should primarily focus on addressing these symptoms effectively.

- **Trend Analysis:** Utilizing the data available from 2000 to 2023, it is possible to analyze the year-wise growth in TBI patients and extrapolate this information to forecast future trends. This analysis can provide valuable insights for healthcare planning, resource allocation, and developing strategies to manage the expected increase in TBI cases.

- **COVID-19 Impact:** Recognizing the decline in response recording since 2020, potentially due to the COVID-19 outbreak, it is important to consider the impact of the pandemic on TBI patient engagement. Efforts should be made to ensure the availability of trained staff and explore alternative methods for patient contact and data collection during challenging circumstances.

- **Vulnerable Head Locations:** The analysis highlights that the back side, front side, and left side of the head are the most vulnerable locations for TBIs. This information can guide preventive measures and safety campaigns to raise awareness about protecting these specific areas during traumatic incidents.

- **Symptom Analysis:** Considering the range of symptoms experienced by TBI patients, it is crucial to conduct an in-depth analysis of these symptoms and their impact on the overall well-being of patients. This can help identify specific areas that require more attention, such as emotional vulnerabilities, cognitive difficulties, physical conditions, and sleep apnea within the medical symptoms category.

- **Model Recommendations:** The Decision Tree and Random Forest models showed promising results in predicting the female class. These models can be further refined and utilized for various applications, such as identifying risk factors, predicting treatment outcomes, or assisting in personalized patient care. Additionally, exploring other classification models could provide additional insights and improve prediction accuracy.

Overall, these recommendations aim to enhance understanding, diagnosis, and treatment strategies for TBI patients based on the insights gained from the analysis.

Future Research

Future research on the above analysis can focus on the following areas:

- **Causal Analysis:** Conducting a causal analysis to identify the underlying factors contributing to the higher prevalence of TBIs among females. This could involve investigating potential gender-specific risk factors, such as differences in lifestyle, occupational hazards, or social and cultural factors that may predispose females to TBIs.
- **Long-term Outcomes:** Explore the long-term outcomes and quality of life for TBI patients, considering factors such as physical and cognitive functioning, emotional well-being, and social integration. Understanding the challenges and needs of TBI survivors beyond the immediate post-injury phase can inform rehabilitation programs and support systems.
- **Treatment Effectiveness:** Assess the effectiveness of different therapies, including applied, alternative, and mental therapies, in improving outcomes for TBI patients. This could involve conducting controlled studies or clinical trials to evaluate the impact of specific interventions on symptom management, functional recovery, and overall well-being.
- **Prevention Strategies:** Investigate effective prevention strategies targeting the leading causes of TBIs, such as accidents, collisions, and assaults. This could involve analyzing injury patterns, and risk factors, and evaluating the efficacy of safety measures, public awareness campaigns, and policy interventions aimed at reducing the incidence and severity of TBIs.
- **Virtual Engagement:** Explore the potential of virtual engagement and telehealth solutions in providing effective care and support for TBI patients, especially during circumstances like the COVID-19 pandemic or other situations that limit direct contact. Assess the feasibility, acceptability, and outcomes of virtual care models in TBI management.
- **Subgroup Analysis:** Conduct subgroup analysis within different age groups to identify age-specific risk factors, symptoms, and treatment needs. Understanding the variations in TBIs across different age cohorts can help tailor interventions and support systems for specific populations, such as children, young adults, or older adults.
- **Machine Learning Models:** Explore the application of advanced machine learning techniques, such as deep learning or ensemble models, to improve the accuracy of predicting TBI outcomes, identifying subgroups with distinct characteristics, or personalizing treatment plans based on individual patient profiles.
- **Data Collection and Standardization:** Investigate the feasibility of establishing standardized protocols for data collection and reporting of TBI-related information across different healthcare settings. This can enhance the consistency and comparability of data, enabling better collaboration, research, and evidence-based decision-making.

By addressing these research areas, we can further enhance our understanding of traumatic brain injuries, improve patient outcomes, and develop targeted interventions to prevent and manage TBIs more effectively.

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