Optimizing Patient Flow and Prioritization in Healthcare:
A Severity-Based Approach
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Optimizing Patient Flow and Prioritization in Healthcare: A Severity-Based Approach

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A R T I C L E I N F O

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A B S T R A C T

The modern healthcare system emphasizes patient-centric care with a focus on timely interventions. This paper addresses the challenges of optimizing patient flow and prioritization in healthcare facilities by advocating for a paradigm shift towards severity-based prioritization. The objective is to identify and prioritize critical cases requiring immediate intervention, thereby enhancing healthcare efficiency and mitigating the risk of adverse outcomes. The classification of patient basis on triage category enables in the identification of order of treatment instead of going for the traditional FCFS method adopted in most of the hospitals today. The study employs machine learning techniques, multivariate data analysis, natural language processing, and data visualization to analyze historical data, identify factors influencing wait times, enhance resource allocation, evaluate customer satisfaction, and forecast future demand. Results indicate significant correlations between patient characteristics, departmental workflow, and wait times, providing valuable insights for improving patient care and resource utilization. Future research directions include advanced machine learning algorithms, enhanced NLP techniques. Since the data used for interpretation is limited, this research confirms how crucial it is to put patient flow optimization as a top priority in the health care sector with view of enhancing patients' results and gratification.

Introduction

Effective coordination of patient movement and prioritization is critical to guarantee adequate access to appropriate care and to use resources efficiently. A way of improving outcomes and the well-being of patients is by efficiently controlling patient queues and ER workflow. Even though traditional methods such as "First Come First Serve" might not be the most effective way of addressing patients' different needs, particularly during periods of high demand.

In view of these problems, this study tries to promote a departure from prioritizing based on the order of arrival in healthcare services for the most vulnerable. Instead of organizing patients based on when they first arrive at the facility, we will group them according to the severity of their illness to recognize and prioritize critical cases that should be immediately dealt with. This approach enhances the efficiency of health care delivery, minimizes the risk of adverse outcomes by ensuring that the most urgent cases receive prompt attention.

For this purpose, we make use of machine learning, multivariate data analysis, natural language processing, and data visualization. These tools help us study past data to detect possible factors that could affect the wait times so that their effect can be predicted. Furthermore, by appreciating the intricate relationship between patient demographics, department workflow, and environmental variables, we can strategically implement interventions aimed at improving the flow of patients as well as the efficient allocation of resources.

Moreover, this study aims to achieve specific objectives, including the improvement of average waiting time optimization, identification of wait time factors, determination of a suitable classifier to prioritize triaging based on severity using multi-objective optimization approaches, investigation of patient sentiments by applying NLP methods, augmentation in resource management techniques, customer satisfaction measurement, and forecasting future demand. By using the literature and advanced analytics, we will be able to gather more information to help us add data from other sources to achieve the main objective of this study on patient flow optimization in healthcare settings. Through evidence-based recommendations and practical insights, we strive to support healthcare practitioners and policymakers in enhancing patient outcomes, improving resource efficiency, and ultimately, delivering patient-centred care.

To reinforce the severity-based approach in patient flow optimization, our investigation will also assess existing scholarly publications for omissions and untapped topics. Then, it will proceed to the description of the methods used in data retrieval, information analytics, and forecasting based on modern analytical technologies. Finally, the results section will illustrate those findings, revealing essential correlations between various items in predictive models and details garnered from the dataset.

To conclude, in summary of essential results and ideas for the healthcare profession, as well as ways to further pursue research, the final chapter will cover these topics. Altogether, these components will help establish a comprehensive understanding of patient flow and prioritization in the healthcare field that can be used to enhance patient outcomes, allocate resources correctly, and improve the effectiveness of a medical establishment.

Literature review and Research Gap

Healthcare system administration is characterized by the process of improving patient flow and prioritization, which is essential to guarantee the provision of timely care services and enhance outcomes. This study investigates the available literature on patient flow optimization, examining multiple research papers that delve into various elements thought to influence the situation in this sphere. It presents the gaps in knowledge that would help with developing future studies on this subject matter.

In a well-known study, an application of new data-driven decision-making methodology was used to manage and establish the priority list of emergency department patients. The investigation highlighted that it is crucial to provide services in a timely manner and to implement sound queue management in situations where the normal course of life or hospital operation has been interrupted by a disaster, such as a COVID-19 infection. By integrating data mining techniques with mathematical modelling and met heuristic algorithms, the study aimed to classify patients, organize queues efficiently, and minimize waiting times. However, gaps were identified in exploring the relationships between the size of the active queue and the quality of care, the use of queuing models to simulate COVID-19 treatment systems, and the handling of server failures in queuing systems.

Another research paper investigated the effect of emergency waiting time on patient satisfaction, utilizing data-driven models and survey methods. The study highlighted the significance of reducing waiting times to enhance patient satisfaction, but identified gaps in measurement tools to assess waiting times' impact accurately and understanding how patient demographics influence perceptions of waiting times and satisfaction levels. Additionally, future research could delve into the long-term effects of waiting times on patient outcomes.

Simulation analyses in primary care settings demonstrated the significant impact of minor modifications to patient arrival and consultation schedules on overall wait times. While previous literature focused on the significance of efficient scheduling and appointment systems, research gaps were found concerning patient waiting times related to other determinants and in terms of operationalizing the theoretical models into practical solutions.

Moreover, the findings of recent research on emergency care for the elderly have underlined the need for swift and well-organized treatment provision, particularly when considering frailty and coordination of care services as part of care delivery. Some areas for further research include identifying the impact of frailty on waiting times and admission rates, assessing integrated care models, exploring patient-centred initiatives, and studying the role of technology in optimizing emergency care.

To sum up, although the current research has contributed important knowledge on how to optimize patient flow and make proper prioritization in the healthcare system, there are still large gaps that require intensive studies. These research gaps need to be closed because only by closing them will we have data that will enable us to come up with evidence-based strategies aimed at ensuring the effectiveness and efficiency of the. The improvement of patient outcomes and experiences is the main purpose of healthcare service delivery.

Methodology

The process entails using a methodology that consists of several steps, aimed at eliciting relevant information from the data and analyzing it with appropriate methods as well as drawing actionable insights for optimizing patient flow and prioritization in healthcare.

Data Collection and Pre-processing:

This part describes the method used to extract the data, pre-process it, select features and build models focusing on machine learning methods and multivariate statistical analysis.

Source Selection:

The dataset was obtained from different government/private medical databases; also reputable online sources were used. In addition to these, research papers and scholarly articles were examined so as to cover all variables associated with patient flow and prioritization adequately.

Data Cleaning:

The dataset underwent careful cleaning before being analyzed to eliminate outliers, inconsistent data entries, missing values etc. Outliers were identified based on statistical criteria or domain knowledge which could be either corrected or eliminated while missing observations were replaced via appropriate means such as mean or median imputation depending upon the nature of the variable involved.

Training Model and Validation:

Data is divided into training and validation to allow the selected models to be trained and their performance evaluated. Cross-validation techniques such as k-fold cross-validation were also used to maintain stability and reduce overfitting. It also has Hyperparameter tuning uses to increase the model efficiency.

Feature Engineering:

Feature engineering techniques are used to improve prediction performance by creating new features or modifying existing features.

Selection of Models:

Here we evaluate various machine learning because the problem is a classification task to find out which model is best for weighting according to importance level of your class. . Support Vector Machines (SVM), Random Forests, Decision Trees and Gradient Boosting Machines (GBM) are some of the algorithms we consider. Performance evaluation, interpretation, and performance evaluation (such as accuracy, precision, recall, F1 score, etc.) determine which model to choose.

Measurement Tests:

Various test methods, including area under the receiver operating characteristic curve (AUC-ROC), regression, indeed, the accuracy and F1 efficiency of this classification model are measured. These metrics measure how well the algorithm categorizes patients into triage groups when addressing critical issues.

Multivariate Data Analysis:

Factor analysis: This technique was applied to demonstrate the potential impact of waiting time on patients. This helps in identifying key factors and optimizations by reducing the amount of parameters associated in dataset into important factors and creating action plan accordingly.

Multiple Linear Regression (MLR): In MLR, multiple independent variables can be used to model average patient waiting time. Useful estimates of wait times can be determined from a variety of other factors, such as patient demographics, complaints, and office performance measurements.

You can understand waiting time analysis by using regression to estimate the coefficients associated with each independent variable to indicate the magnitude and direction of the effect. This allows healthcare managers to focus on interventions that have the greatest impact on patient performance.

Discriminant Analysis: Discriminant analysis is used to distinguish between various classifications based on a combination of patient characteristics and clinical parameters. This analysis helps create decision making policies that draw boundaries between crisis and prioritize them according to their severity. The discrimination created by this analysis can classify new cases into appropriate classifications and ensure timely response to important cases when resource allocation and operational management are improved.

Cluster Analysis: This technique is used to find specific groups or groups of patients who share common or clinical patterns. Cluster analysis helps identify special or at-risk groups of patients with similar symptoms by grouping patients based on factors such as complaints, vital signs, and clinical outcomes.
It uses classification techniques to divide data into homogeneous groups to help plan interventions and individual care. This improves healthcare by tailoring treatments and resources to each patient's unique needs.

Integration and Interpretation:

This multidisciplinary approach complements the classification model by providing additional information regarding the interaction between patient characteristics, office work, and environment. By combining the results of MLR, discriminant analysis, and cluster analysis, healthcare providers can develop comprehensive strategies to accurately and prioritizely improve patient outcomes. Interpretation of these analyzes can lead to recommendations to guide healthcare administrators in the use of evidence based interventions designed to improve patient outcomes, improve resource allocation, and deliver patient care.

Results

1: Machine Learning: It is an effective tool to improve patient care and improve hospital operations. In improving healthcare, machine learning (ML) models can evaluate large amounts of patient data, predict diseases, recommend treatment plans, and leverage all currently available resources. Doctors can use machine learning technology to increase efficiency, increase patient satisfaction, and most importantly, improve patient outcomes. In this study, we used machine learning (ML) to develop predictive models that lead to timely intervention, reduced emergency room wait times, and improved quality of care in hospitals.

Analysis has been done through learning to model predictions using a variety of machine learning methods, including support vector machines (SVM), gradient booster classifiers, decision trees, random forests and logistic regression. Performance parameters were used to evaluate each model's ability to predict triage classes based on patient characteristics such as precision, accuracy, recall, confusion matrix, and F1 score.

1.1.Logistic Regression:

On the testing dataset, the accuracy of the Logistic Regression model was 35%. The following were the F1-score, recall, and precision for each triage category:
• Triage Category 0: F1-score = 0.00, Precision = 0.00, and Recall = 0.00
• Triage Category 1: F1-score = 0.41, Precision = 0.28, Recall = 0.75
• Triage Category 2: F1-score = 0.36, Precision = 0.62, Recall = 0.25
With poor recall and precision, the model performed especially poorly when it came to predicting Triage Category 0. Although Triage Category 1 performance was improved, the total accuracy was still not very high.

1.2. Decision Tree:

A 35% accuracy rate was also attained by the Decision Tree model. For every triage category, the following were the precision, recall, and F1-score:
• Triage Category 0: F1-score = 0.43, Precision = 0.50, Recall = 0.38
• F1-score: 0.47, Precision: 0.32, Recall: 0.83, Triage Category 1:
• Triage Category 2: F1-score = 0.09, Precision = 0.33, and Recall = 0.05

With a comparatively higher precision and recall than other categories, the Decision Tree model performed better for Triage Category 1. It had trouble accurately categorizing incidents in Triage Category 2, though.

1.3.Random Forest:

With 30% accuracy, the Random Forest model produced results. For every triage category, the following were the precision, recall, and F1-score:
• Triage Category 0: F1-score = 0.00, Precision = 0.00, and Recall = 0.00
• Triage Category 1: F1-score = 0.46, Precision = 0.31, and Recall = 0.92
• Triage Category 2: F1-score = 0.08, Precision = 0.25, and Recall = 0.05

Random Forest performed moderately for Triage Category 1 and suffered with Triage Category 0, much like Logistic Regression. It also had trouble accurately anticipating incidents in Triage Category 2.

1.4.Support Vector Machine (SVM):

Similar to Random Forest, the SVM model attained a 30% accuracy rate. For every triage category, the following were the precision, recall, and F1-score:
• Triage Category 0: F1-score = 0.00, Precision = 0.00, and Recall = 0.00
• Triage Category 1: F1-score = 0.46, Precision = 0.30, and Recall = 1.00
• Triage Category 2: F1-score = 0.00, Precision = 0.00, and Recall = 0.00

For Triage Category 1, SVM demonstrated high recall, accurately identifying the majority of cases in this category. But it had trouble classifying occurrences in Triage Categories 0 and 2 accurately, and it had difficulty with precision across the board.

1.5.K-Nearest Neighbors (KNN):

This model yielded an accuracy of 30%. Precision values for triage categories 0, 1, and 2 were 0.00, 0.27, and 0.50, respectively. Recall values were 0.00, 0.92, and 0.15, and F1-scores were 0.00, 0.42, and 0.24 for the corresponding categories. While the model exhibited reasonable precision for triage category 2, its overall performance was lower compared to other models.

1.6. Gradient Boosting Classifier:

It has an accuracy of 40%, the Gradient Boosting Classifier proved to be the most effective model among those put to the test. For every triage category, the following were the precision, recall, and F1-score:
• Triage Category 0: F1-score = 0.00, Precision = 0.00, and Recall = 0.00
• Triage Category 1: F1-score = 0.49, Precision = 0.33, Recall = 0.92
• Triage Category 2: F1-score = 0.37, Precision = 0.71, Recall = 0.25
Across all triage categories, the Gradient Boosting Classifier performed the best, with the highest accuracy. It performed exceptionally well in predicting Triage Category 1, demonstrating great recall and precision in identifying individuals requiring urgent care.

```
Gradient Boosting Classifier:
Accuracy: 0.40
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         8
           1       0.33      0.92      0.49        12
           2       0.71      0.25      0.37        20

    accuracy                           0.40        40
   macro avg       0.35      0.39      0.29        40
weighted avg       0.46      0.40      0.33        40

==================================================
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Comparing the performance of all models, the Gradient Boosting Classifier stands out as the most effective in predicting the triage category based on patient attributes. It achieved the highest accuracy of 40% and showed balanced precision and recall across the triage categories.

2: Multivariate Data Analysis

This technique plays a crucial role in this project by enabling a comprehensive examination of various factors influencing patient flow and prioritization in healthcare facilities. The scope of MDA encompasses several sub-domains, each contributing unique insights and facilitating evidence-based decision-making.

2.1. MLR(Multiple Linear Regression)-FIT MODEL

Dependent Variable (Y): Average Wait Time (Minutes)

Independent Variables (X):
- Triage Category
- Arrival Rate (patient/hour)
- Occupancy Rate
- Treatment Cost (INR)
- Age

Effect Summary

Click-and-drag the axis to pan or zoom.

Source	Logworth	PValue
Triage Category	15.928	0.00000
Arrival Rate (patient/hour)	3.231	0.00059
Occupancy Rate	1.918	0.01209
Treatment Cost (INR)	1.769	0.01702
Age	0.506	0.31155

In summary:
 "Triage Category" and "Arrival Rate" have highly significant effects on "Average Wait Time."
 "Occupancy Rate" and "Treatment Cost" also have statistically significant effects, but their significance is somewhat lower.
 "Age" does not have significant effect on "Average Wait Time"

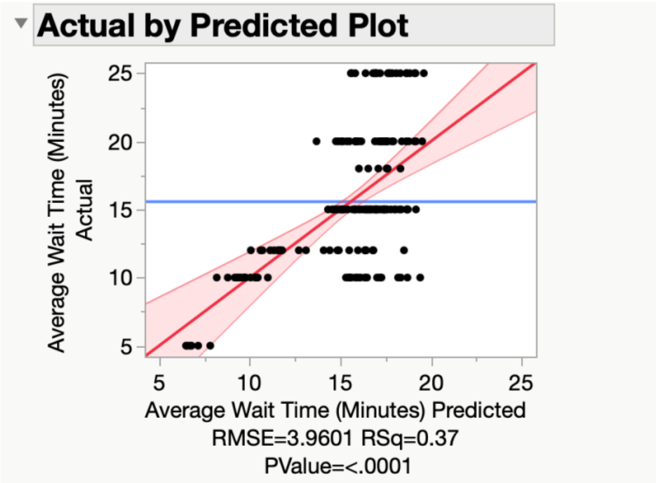
Summary of Fit

RSquare	0.365607
RSquare Adj	0.345885
Root Mean Square Error	3.960099
Mean of Response	15.57
Observations (or Sum Wgts)	200

$R^2 = 0.365607$ indicates that approximately 36.56% of the variability in the "Average Wait Time" is explained by the independent variables in the model.

Adj $R^2 = 0.345885$ is slightly lower than R^2 and suggests that, accounting for model complexity, around 34.59% of the variability in the "Average Wait Time" is explained.

The average prediction error in the units of the dependent variable ("Average Wait Time") is expressed as RMSE = 3.960099. The model's average forecast error in this instance is 3.96 minutes, which is less than the desired minimum root mean square error (RMSE).



The discrepancy between the actual and anticipated average wait durations is displayed in the scatterplot. Every point on the plot represents one observation. The red line, or regression line, illustrates the linear relationship between the two variables that most closely matches the data.

The average wait time variance is 37% an R-squared of 0.37. The root mean squared error (RMSE) of 3.96 minutes indicates that the average prediction was 3.96 minutes off taking everything into account, the model seems to be able to predict the average wait time very well.

2.2. Factor Analysis

Test of Kaiser-Meyer-Olkin (KMO):

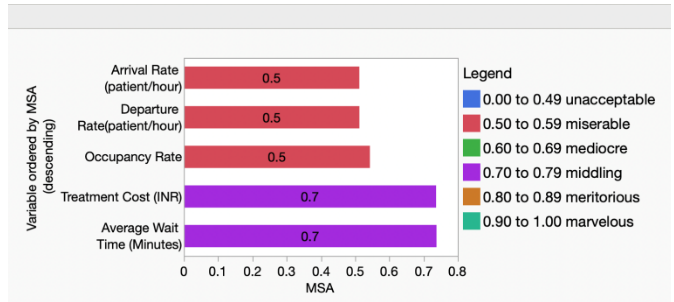
It is a tool for evaluating how well a sample is chosen for factor analysis. This statistic shows the percentage of variance in a set of variables that could represent common variance. It's common to regard a KMO rating above 0.5 to be acceptable.

Kaiser-Meyer-Olkin Test

	MSA (Measure of Sampling Adequacy)
Arrival Rate (patient/hour)	0.513
Average Wait Time (Minutes)	0.738
Departure Rate(patient/hour)	0.513
Occupancy Rate	0.543
Treatment Cost (INR)	0.737
Overall MSA	0.523

All the mentioned factors have KMO value greater than 0.5 which means all these factors have significant impact in optimizing patient flow and prioritization for emergency department.

Average waiting time (min) and Treatment cost (INR) have the highest KMO which means that these factors that is most likely to be explaining the variability.



Factor 1 represents "Patient Flow" suggests that a higher count of patients arriving at the emergency department section is strongly associated with this factor. The negative loadings on the other variables imply that higher patient flow is linked to shorter wait times, faster departure rates, lower occupancy rates, and lower treatment costs. This might be because when more patients arrive, the hospital is forced to be more efficient in processing them to reduce congestion.

Factor 2 signifies "Resource Utilization", suggests that this factor is related with the overall throughput of the count patients in the emergency department. The negative loadings on the other variables indicate that higher resource utilization is linked to shorter wait times, lower occupancy rates, and lower treatment costs. This might be because when the hospital can efficiently process patients through the system, it reduces congestion and wait times.

Standard Score Coefficients

	Factor 1	Factor 2
Arrival Rate (patient/hour)	0.938138	0.797176
Average Wait Time (Minutes)	-0.032150	0.393077
Departure Rate(patient/hour)	0.057130	-0.698497
Occupancy Rate	0.016901	-0.206643
Treatment Cost (INR)	0.018051	-0.220697

Variance Explained by Each Factor

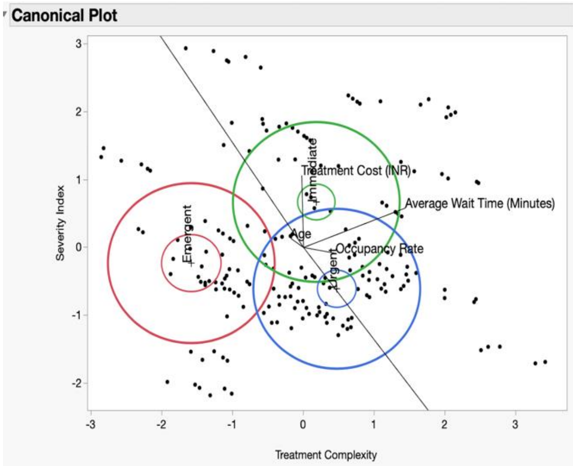
Factor	Variance	Percent	Cum Percent
Factor 1	2.0414	40.828	40.828
Factor 2	0.3527	7.054	47.881

2.3. Discriminant Analysis

Dependent Variable: Triage Category

Independent Variable:

- Age
- Arrival Rate (Patients/hour)
- Average Wait Time(Minutes)
- Occupancy Rate
- Treatment Cost(INR)21
- Departure Rate(Patients/hour)



“Severity Index” captures the urgency of medical need.
“Treatment Complexity” reflects the anticipated demands on hospital resources.

The canonical plot suggests a relationship between severity index and treatment complexity, implying a potential correlation between patient triage category and factors such as age, arrival rate, wait time, occupancy, cost, and departure rate.

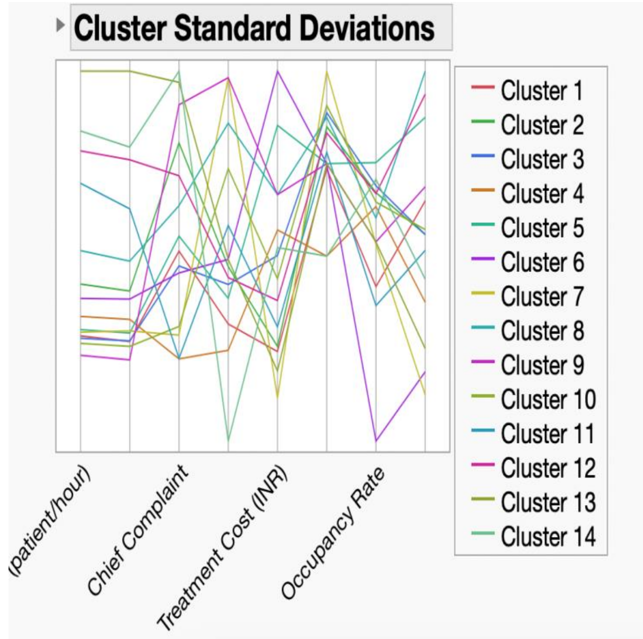
The model has a low FPR and a high TPR over a broad range of thresholds, as indicated by the ROC curve. This indicates that while avoiding a large number of false positives, the model is able to accurately identify positive situations (such as emergent, immediate, and urgent triage categories). With a ROC score (AUC) of 0.974, the performance is deemed excellent.

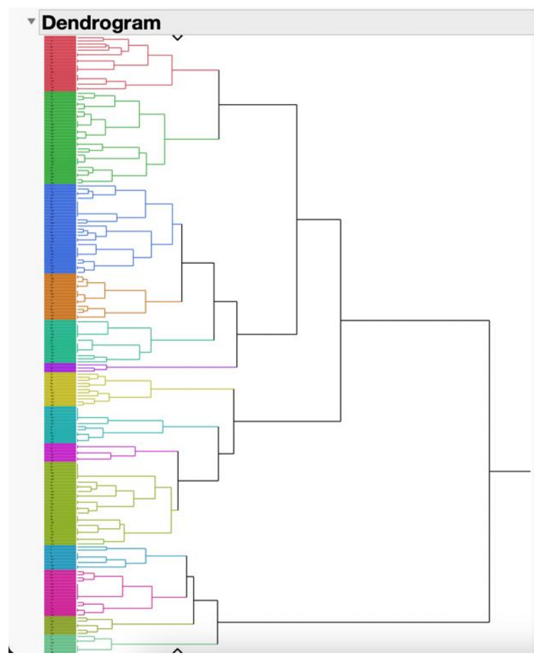
Test	Value	Approx. F	NumDF	DenDF	Prob>F
Wilks' Lambda	0.480023	14.1869	12	384	<.0001*
Pillai's Trace	0.6115779	14.1689	12	386	<.0001*
Hotelling-Lawley	0.8924073	14.2260	12	295.6	<.0001*
Roy's Max Root	0.5371524	17.2784	6	193	<.0001*

The Wilks' Lambda test indicates significant discrimination power of the model ($p < 0.0001$). It suggests that the combination of independent variables effectively differentiates between triage categories in healthcare based on severity and treatment complexity.

2.4. Cluster Analysis

Cluster Analysis plays a pivotal role in understanding patient characteristics, identifying distinct patient groups, and tailoring healthcare interventions to specific needs. In this project, Cluster Analysis has been conducted on the dataset containing various parameters related to patient demographics, medical conditions, and treatment outcomes. Specifically, 14 clusters have been generated to segment the patient population based on similarities in their attributes.





This chart shows the difference in four characteristics for each group: major complaints, medical costs, occupancy rate and arrival rate. The degree of dispersion of the data in each group is represented by the standard deviation. When a group of data points has a lower standard deviation, they are closer together; they are more spread out when their standard deviations are higher.

In the context of patient wait times, a low standard deviation for a group may indicate that factors are causing variation in wait times. Pain is rare in the group. This will help identify areas where patient wait times can be reduced.

3: Natural Language Processing

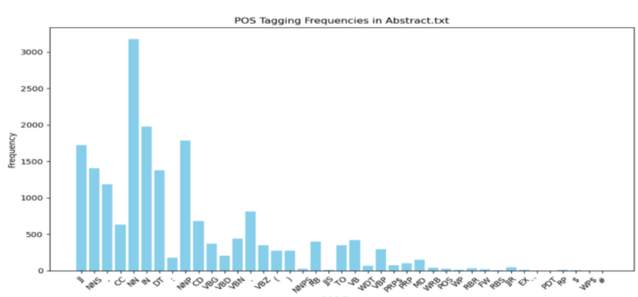
Natural Language Processing (NLP) is revolutionizing medical optimization technology. Doctors can use natural language processing (NLP) technology to analyse patient reviews, medical records, and appointment information to improve patient outcomes and the severity of emergencies. NLP makes it possible to gather meaningful information from unstructured data to help patients cognitively think, explore, and improve in treatment. In this study, we use the NLP method to improve time management in healthcare and focus on important factors that will reduce waiting time and improve the patient's outcome effect.

3.1. Tokenization and Lemmatization

The text was tokenized and lemmatized to prepare it for further analysis. Tokenization resulted in a total of 23,576 tokens, with lemmatization reducing this to 19,942 unique lemmas.

Part-of-Speech (POS) Tagging

POS tagging was performed to analyze the distribution of different grammatical categories within the text. The most frequent POS types identified are shown in the graph



3.2. Topic Modelling: To determine the text's underlying themes, topic modeling with Latent Dirichlet Allocation (LDA) was utilized. Three primary subjects surfaced from the examination:

Topic 0: Patient Care and Satisfaction

- Top Words: patient, model, satisfaction, ED (Emergency Department), care, health, study, service, time

This topic seems to focus on patient care and satisfaction, possibly related to healthcare models, emergency department experiences, and healthcare services.

Topic 1: Healthcare Models and Studies

- Top Words: model, satisfaction, health, study, ED, service, care, wait, time

Topic 1 appears to revolve around healthcare models, patient satisfaction studies, health services, and possibly the wait times in healthcare settings.

Topic 2: Patient Satisfaction and Care

- Top Words: patient, satisfaction, model, ED, care, wait, data, time, service, simulation

This topic focuses on patient satisfaction, healthcare models, emergency department care, data analysis, and service simulation.

3.3. Sentiment Analysis

- Compound Score: 0.8748
- Sentiment: Positive

Analysis of Results

The analysis of the text reveals a diverse distribution of parts of speech, with a significant emphasis on nouns, particularly related to patient care and healthcare services. Adjectives and verbs also play a notable role, likely describing the characteristics and actions within the healthcare context.
The three topics identified through LDA provide insights into the primary themes of the text. Topic 0 centres on patient care and satisfaction, possibly indicating a study or analysis of patient experiences in healthcare settings.

Topic1 demonstrates a focus on health care models an d research, showing research on the effectiveness or u se of different treatment models.
Topic 2 focuses on patient satisfaction and care and m ay explore data analytics and simulation services to im prove the patient experience.

Analysis shows that a positive feeling is present in the text, the analyzed speech and content show a positive f eeling or attitude about the topic. These findings provi de insight into key themes, major themes, and insights in the text, providing a broader perspective on the research or discussion presented.

Conclusion

Our research on optimizing patient and healthcare delivery through critical care systems insights to improve health and improve patient outcomes. From recommending changes to prioritizing, this study addresses the challenges of managing patient groups, improving ED performance, and ensuring timeliness.

Through machine learning techniques, data analytics, natural language processing and data visualization, we analyze historical data, analyze trends affecting wait times, improve resource allocation, measure customer satisfaction and predict future demand. possible. Identification of patients by triage severity category allows prioritization of important cases requiring urgent intervention, thereby reducing the risk of adverse outcomes and improving health.

Results show that prioritizing patient optimization in treatment is critical to improving patient outcomes. Improve the use of resources and provide centralized patient care. By integrating insights from existing data, using advanced analytical techniques, and leveraging customer feedback, this research provides useful information for physicians and policymakers to improve services and meet patients' needs.

Limitations:

Despite the significant contributions of this study, some limitations must be acknowledged:

Data Quality and Interpretation: Data quality and interpretation may be affected by bias, missing data, and inconsistencies in the medical record. To ensure the validation and correctness of the results, these limitations must first be addressed and data cleaning must be performed.

Generalizability: The results of this study can only be applied to the study's specific clinical and patient population. It is important to carefully analyze content needs, differences in health standards, and the patient's circumstances. demographics before extrapolating the findings to other locations or populations.

Model Complexity: The complexity of the applied process and machine learning models used in research may make it difficult to implement and interpret. It can only be supported by stakeholders and practitioners by simplifying the model and clarifying the decision-making process.

Future Scope

Although this study focuses on improving patient and healthcare outcomes, it may not fully address all aspects of the work or include common procedures that impact patient outcomes. Future research should explore multidisciplinary approaches and consider interactions between environmental, social, and economic factors that influence health.

Despite these complaints, the results of the study support the positive experiences of patients working effectively in medical facilities and provide the basis for further research and development of cultural practices

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