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Enhancing Patient Experience by Automating and Transforming Free Text into Actionable Consumer Insights: A Natural Language Processing (NLP) Approach

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ABSTRACT

Background: The digitalization of healthcare has expanded patient access to care delivery through various virtual platforms. These platforms accumulate a wealth of patient feedback data, offering valuable insights into care perception and experience. Natural Language Processing (NLP) provides a means to efficiently analyze this unstructured patient feedback, enabling healthcare organizations to enhance care quality and patient experience.
Methods: This study collected 19,000 comments from diverse sources, including surveys and social media, spanning from January 1, 2018, to June 30, 2021. The data underwent preprocessing, including lowercase conversion, special character removal, and lemmatization. A "hot word" list was employed to identify critical patient safety concerns. NLP models, including sentiment analysis and text classification, were used to analyze patient feedback.
Results: The sentiment analysis revealed that most patient comments were positive or neutral, with 34.5% positive, 52.6% negative, and 12.9% neutral sentiments. Aggregate analysis identified access and login issues as a primary source of dissatisfaction, with 78% of related comments expressing negativity. The study also utilized Word2Vec to uncover word associations, highlighting positive associations with "staff" and negative associations with "website" and "insurance." Hot word detection identified 580 comments requiring immediate attention for patient safety.
Conclusions: NLP-enabled analysis of patient feedback offers actionable insights for healthcare organizations. It identifies areas for improvement, tracks sentiment trends, and aids in patient engagement. Additionally, NLP benefits research and development by accelerating drug discovery and improving healthcare outcomes. Despite limitations, NLP's role in healthcare data analysis is poised to grow, benefiting both providers and consumers. This study recommends proactive use of NLP tools to enhance care delivery and patient experience.

Keywords: Natural Language Processing, Context-aware Algorithms, Quality Improvement Framework, Text Classification, Electronic Health Records, Machine Learning, Word2Vec, Sentiment Analysis, Word2Vec, Hot Word List, Frequency Distribution, Patient Feedback.

INTRODUCTION

Digitalization of healthcare has opened patient access patients of care delivery. From traditional model of care delivery that was confined to hospital and clinics, patients can now access care via mobile apps, websites, text messages, and other virtual and ambulatory platforms. Having different access points provide convenience and enables organization to look at users of healthcare services not just as patients but consumers of healthcare. These different channels/platforms now hold tremendous amount of consumer/patient feedback data that is not required to be reported to any regulating agency like the Center of Medicare and Medicaid Services (CMS) but holds valuable insights regarding perception and experience of care. A good patient centric approach for organizations and stakeholders is to analyze this available data on their platform and integrate the patient needs into care to enhance overall experience and quality.

Patient feedback can be obtained as open ended, closed ended questions or a combination of both. Closed ended are well-structured questionnaire and yields quantitative results that are easy to analyze. However, open ended feedback coming directly from patients is in natural language and raw text form, making it difficult to manually analyze especially if thousands of comments are submitted in a day.

Thus, for large health systems to better utilize the staffing resources, us Natural Language Processing (NLP) algorithms makes it convenient and feasible. NLP also enables to objectively differential between mixed comments that carry mixed sentiments. A good example of this is a patient saying, “Doctor was good, but the staff treated me horribly” If we ask two different people to rate the sentiment one can classify the care experience as good (since the doctor was good) however, another individual can classify the same feedback as extremely negative as the patient used the word “Horrible”. In such scenarios NLP algorithms combines both good-bad sentiments to provide an objective score on one single scale [1].

NLP Application in US Healthcare

Healthcare generates an enormous volume of data daily, including electronic health records (EHRs), patient reviews, social media posts, and medical literature. NLP leverages advanced algorithms to analyze and understand this unstructured textual data, enabling healthcare providers, insurers, and pharmaceutical companies to gain valuable insights into consumer behavior, preferences, and needs.

One of the primary ways NLP is used in healthcare is through sentiment analysis of patient reviews and social media posts. By analyzing the sentiment of patients' feedback and opinions, healthcare organizations can gauge patient satisfaction and identify areas that require improvement [2]. For example, if multiple patients express dissatisfaction with long wait times in a hospital's emergency department, administrators can take action to address this issue promptly [3]. Moreover, NLP can be employed to extract valuable insights from medical literature. Researchers can use NLP algorithms to identify emerging trends, drug interactions, and potential side effects mentioned in scientific articles and clinical trials. This information can guide pharmaceutical companies in drug development and help healthcare providers make informed decisions about treatment options.

Another crucial application of NLP in US healthcare is in the analysis of electronic health records. These records contain a wealth of information about patients' medical history, symptoms, diagnoses, and treatment outcomes. NLP algorithms can extract structured data from these records, allowing healthcare professionals to identify patterns and trends. For instance, NLP can assist in identifying patients with a higher risk of a particular condition based on their medical history, which can lead to targeted preventive interventions.

NLP also plays a significant role in improving patient engagement and communication. Chatbots powered by NLP can answer patients' questions, schedule appointments, and provide medication reminders. These virtual assistants can enhance the overall patient experience and ensure that patients have access to relevant information when they need it.

Furthermore, NLP can assist in identifying potential outbreaks and monitoring public health trends in US. By analyzing social media posts and news articles, NLP algorithms can detect early signs of infectious diseases or adverse reactions to medications. This information can be used to alert public health authorities and initiate timely interventions to prevent the spread of diseases.

US healthcare insurers can also benefit from NLP-driven insights. By analyzing customer interactions and claims data, insurers can identify fraud patterns, predict high-risk individuals, and tailor their offerings to better meet customer needs. This not only helps in reducing fraudulent claims but also in improving customer satisfaction.

In addition to its direct applications, NLP in healthcare also has significant implications for research and development in US. It can accelerate the drug discovery process by analyzing vast amounts of scientific literature to identify potential drug candidates, target proteins, and relevant research papers. This can lead to faster and more cost-effective drug development within the pharmaceutical industry in US, ultimately benefiting patients.

Natural Language Processing has revolutionized the healthcare industry by enabling the extraction of actionable consumer insights from unstructured text data. From sentiment analysis of patient reviews to the analysis of medical literature and electronic health records, NLP empowers healthcare organizations to make data-driven decisions, enhance patient engagement, and improve overall healthcare outcomes. As the healthcare industry continues to generate massive amounts of textual data, the role of NLP in generating actionable insights is poised to grow even further, ultimately benefiting both healthcare providers and consumers alike.

METHODS

The methods employed in a Natural Language Processing (NLP) study for healthcare are a critical component, as they form the foundation for the systematic analysis of patient feedback data and textual information from various sources. These methods are essential for transforming unstructured text into valuable insights that can drive improvements in healthcare services, patient experience, and overall care quality.

The background of these methods is rooted in the growing digitalization of healthcare, which has opened new avenues for patient access to care delivery. In the past, healthcare services were primarily confined to traditional settings such as hospitals and clinics. However, with the advent of digital technologies, patients can now access healthcare through a plethora of virtual platforms, including mobile apps, websites, and text messages. This transformation has not only provided convenience to patients but has also transformed them into consumers of healthcare services. Consequently, healthcare organizations and stakeholders are increasingly recognizing the importance of analyzing the feedback generated through these digital channels to enhance patient-centric care.

Patient feedback comes in various forms, including open-ended comments and structured closed-ended questions. While closed-ended questions yield quantitative results that are relatively straightforward to analyze, open-ended feedback poses a unique challenge. These comments are expressed in natural language and raw text, making manual analysis a daunting task, particularly when dealing with thousands of comments daily. Thus, the need for advanced NLP algorithms becomes apparent, as they offer a convenient and feasible solution to process and extract meaningful information from large volumes of unstructured text data.

To effectively utilize NLP in healthcare, data preprocessing is essential. This initial step is vital for standardizing the text and preparing it for subsequent analysis. Preprocessing actions include converting all text to lowercase, as algorithms treat words with different letter cases as distinct. Special characters and numbers are removed to streamline the text. A crucial technique employed during preprocessing is lemmatization, which transforms words into their common or base form while preserving their core meaning. Unlike stemming, which truncates words and may produce non-words, lemmatization provides linguistically accurate and meaningful results. In the context of patient feedback data, where terms like "doc," "dr," and "doctor" are common, lemmatization reduces redundancy by substituting synonyms with a single term, typically "doctor." Additionally, stop word elimination simplifies the dataset by removing non-essential words, allowing the analysis to focus on the most relevant content.

Beyond these preprocessing steps, methods for dealing with specific challenges in patient-derived data are crucial. Patients may lack healthcare literacy, leading to spelling mistakes and the use of informal text language that may not be covered by standard NLP libraries. These challenges necessitate a comprehensive preprocessing approach to ensure the accuracy and reliability of subsequent analysis.

The methods utilized in NLP studies for healthcare are a multifaceted approach to transforming unstructured text data into actionable insights. These methods encompass data preprocessing, text classification, sentiment analysis, Word2Vec analysis, and hot word detection. They address the challenges posed by patient feedback data and empower healthcare organizations to make data more actionable. The paper talks about such methods in much more detail with respect to the specific study below.

Data Collection

For the purpose of the study 19,000 comments were collected from Press Ganey: HCAHPS and CGCAHPS Surveys, C-SAT-Survey, CareDash, Facebook, Google, GooglePlayStore, HealthGrades, Product Survey, Instagram, MyChart, RateMDs, Twitter, Vitals, Wellness, YP.com, ZocDoc between January 1, 2018 and June 30, 2021. No patient names were visible to the researchers. Names of employees occasionally appeared in some of the comments but were removed during preprocessing. This database constituted the raw data for subsequent analysis.

Data Preprocessing

Textual data preprocessing represents the initial and crucial step in text and document classification model enhancement. Its primary objective is to standardize the text, optimizing subsequent analysis. This process encompasses several key actions, including the conversion of all text to lowercase, a crucial step since algorithms treat "Doctor" and "doctor" as distinct words. Additionally, special characters and numbers are removed, streamlining the text for analysis. In this study we utilize lemmatization to transform words into a common, simplified form while still maintaining their core meaning. Lemmatization is a natural language processing (NLP) technique that involves reducing words to their base or dictionary form, known as a "lemma." This is particularly useful for text analysis, information retrieval, and language processing tasks where word normalization is necessary.

In contrast to stemming, which truncates words to their root form by removing prefixes and suffixes (sometimes resulting in non-words), lemmatization aims to provide valid words that exist in a language's dictionary. As a result, lemmatization produces more linguistically accurate and meaningful results compared to stemming.

In the context of this study, which involved raw patient text data, several common terms like "doc," "dr," and "doctor" were prevalent. To mitigate redundancy and enhance statistical validity, these synonyms were replaced with a single term, typically "doctor." This substitution reduces the overall number of terms, preventing unnecessary duplication of information.

Furthermore, certain words, often referred to as "stop words," contribute little to the text's meaning. As part of the preprocessing pipeline, we conducted stop word elimination to streamline the dataset further. By removing these non-essential words, we aimed to simplify the dataset and focus on the most relevant and informative content for analysis. This comprehensive preprocessing approach lays the foundation for more effective and accurate text and document classification models, ultimately improving the overall performance of our analysis.

```
In[5]:

# these function is going to clean the responses.
def clean_responses(text):

    nlp = English()
    my_doc = nlp(text)

    # getting the tokens
    token_list = [token.text.lower() for token in my_doc]

    # adding elements to the libraries stop words list
    # adding elements to the libraries stop words list
    my_stop_words = ['.',',',' ', '(', ')', 'the', 'The.','is','in','what','a','where', 'place', 'gone','feel','like', 'having','test','on',
                     'aziengbe', 'daughter','make','need', 'small','This','this','My','my','mine', 'have','iã', 'iã ', 'yes','tried', 'thr', 'donã', 'day', 'needs',
                     'understand', 'texas', 'donã ', ' donã','ts', 'canã ','canã',' canã', ' iã', 've','donã',' donã ']
    for stopword in my_stop_words:
        lexeme = nlp.vocab[stopword]
        lexeme.is_stop = True

    filtered_sentence = []
    for word in token_list:
        lexeme = nlp.vocab[word]
        if lexeme.is_stop == False:
            filtered_sentence.append(word)

    return ' '.join(filtered_sentence)
```

Figure 1: code function utilized for lemmatization.

Examples

- Grammatical and plural variations were made consistent. Example: doctors -> doctor, nurses -> nurse, went -> go, saw -> see, happened -> happen
- Abbreviations / Alternate Spellings - Few commonly used abbreviations/ alternate spellings were made consistent. Examples: dr -> doctor, emergency room -> er, texas health -> thr, web site -> website

Text Classification

This study also utilized text classification which is a fundamental natural language processing (NLP) technique, by which we automatically categorized and organized textual data into predefined classes or categories. In the healthcare context, text classification is employed to make sense of a wide range of textual information, including electronic health records (EHRs), patient notes, clinical reports, research articles, and more.

The first step involves gathering healthcare-related textual data from various sources. This diverse data may include medical records, physician notes, radiology reports, and scientific literature. Text preprocessing is crucial, as it prepares the data for analysis. Tasks like tokenization, stop word removal, and stemming or lemmatization standardize the text, making it suitable for machine learning models. Labeling and annotation create a labeled dataset where domain experts assign predefined categories or labels to each document. For example, documents can be categorized as "cardiology," "oncology," "patient records," or other relevant classes. Feature extraction transforms the preprocessed text into numerical representations that machine learning models can process. Common techniques include TF-IDF and word embeddings.

The choice of machine learning algorithm or deep learning model depends on the specific task and dataset. Models like Naive Bayes, Support Vector Machines, or advanced deep learning models like Transformers were employed. Once trained and evaluated, the text classification model can be deployed to automatically categorize incoming healthcare documents. This automation streamlines processes, enhances decision-making, and facilitates information retrieval, ultimately improving healthcare delivery and patient care.

Sentiment Analysis

Further in the NLP study, Sentiment Analysis serves as a vital methodology to gain valuable insights from textual data, particularly in understanding the sentiments expressed in patient comments and feedback. This analysis employs a two-fold approach, involving the disaggregation of comments and subsequent aggregate analysis to uncover meaningful patterns and trends.

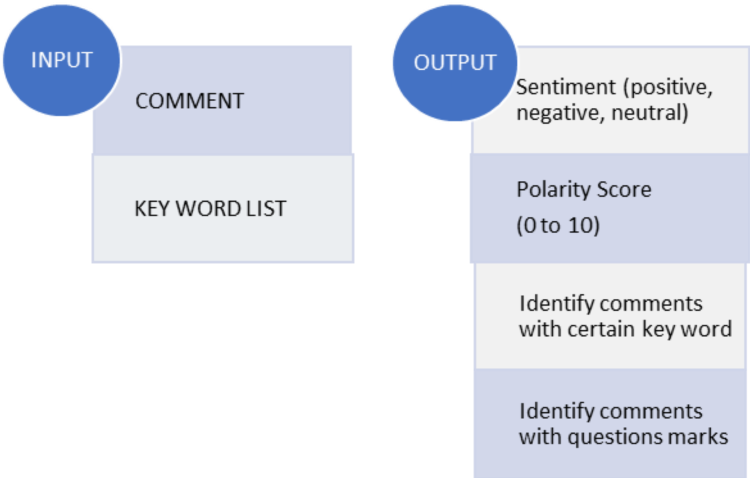

Figure 2: Input and output parameters for Sentiment Analysis.

The initial step in Sentiment Analysis involved sentiment classification for each individual comment. This means assigning a sentiment label, such as Positive, Negative, or Neutral, to each comment based on the emotional tone expressed. Moreover, a polarity score ranging from 0 to 10 is assigned to quantify the intensity of sentiment within the comments. These labels and scores help in gauging the overall sentiment landscape within the healthcare data.

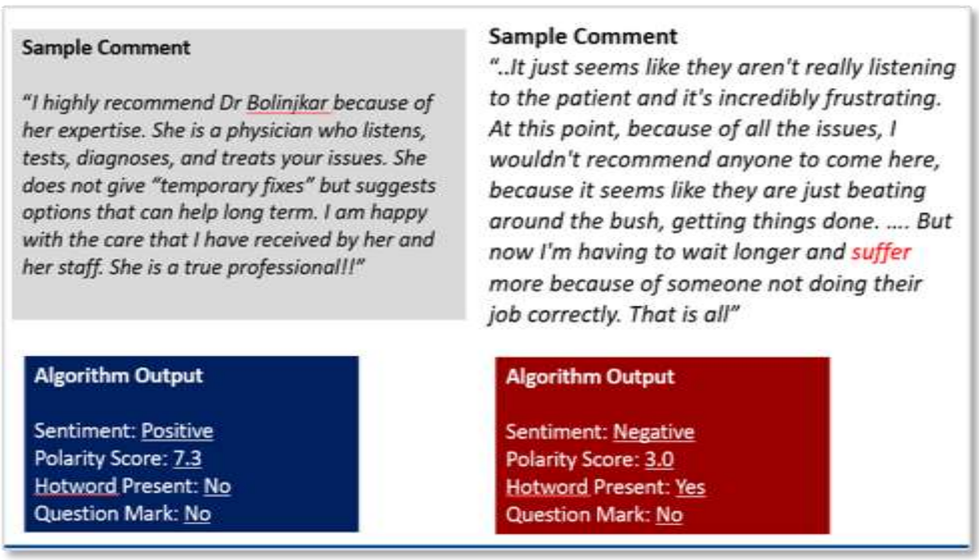

Figure 3: Sentiment Analysis output examples.

The analysis goes further by identifying top words within the comments, shedding light on frequently occurring terms that are indicative of prevalent sentiments. Part of Speech (POS) tagging is utilized to distinguish nouns, verbs, and other grammatical components, aiding in a more comprehensive understanding of the linguistic aspects of sentiment. Furthermore, the study employed the identification of context words, specifically targeting mentions of certain words like "doctors, "website", “information”, “pay”. This contextual analysis allows researchers to discern what sentiments are being expressed concerning these critical healthcare-related topics, providing actionable insights for healthcare providers and organizations.

Figure 4: Examples of category identification output based on keywords in comments.

Other Identified categories were:

```
# Create keyword list
Access = ['account', 'signing', 'sign', 'username','password', 'passwords', 'logins', 'login', 'access',
         'activation', 'user', 'user id', 'log', 'sighin', 'card', 'id', 'accounts', 'mail', 'reset',
         'logging', 'social security', 'security number', 'app', 'user friendly','pass word']
Appointment = ['appointment','scheduling','scheduled','appt','schedule','rescheduled','appointments','appoints']
Drug = ['drug','drugs']
Customer_care = ['care','customer service','customer','satisfied','caring']
Health_patients=['health','patient','medical','patients','medicine','medicines','medication']
Information = ['information','phone','email','gmaail','gmail','message','info','emails','form','forms',
              'documents','document']
Covid = ['covid', 'vaccine', 'vaccination', 'dose', 'shot', 'vaccinations']
Terms = ['terms']
Bill = ['payment', 'bill','Bill','pay','charged']
Prescription = ['prescription','prescriptions','Prescription','Prescriptions']
App = ['chart','Chart','website','web','websites','view','system','site','saved','data','code','cursor','entered',
      'enter','real time','entries','unresponsive','functional','on line','upload','dashboard']
test_results = ['test','results','lab','labs','Lab','Labs','tests','Test']
Insurance = ['Insurance','insurance']
Doctor = ['Doctor','doctor','Dr','dr','Clinician','clinician','Clinicians','clinicians','Dr.','dr.']
```

Figure 5: sample code to create multiple categories for the NLP study.

To facilitate this comprehensive sentiment analysis, a Sentiment Classification Tool was developed. This tool utilizes two distinct approaches. The first approach inputs comments and a list of “key” or "hot" words, subsequently generating sentiment labels and polarity scores for each comment. Additionally, it identifies comments containing specific keywords and those with question marks, offering a more nuanced perspective on sentiment nuances and potential areas of concern within the healthcare dataset.

One of the key problems solved during this approach was to flag and respond to high priority patient comments where urgent response is required. This was done by creating a “Hot Word” list. The list intentionally was spelled incorrectly to mimic usual typing behaviors. The list contained words “abuse, neglect, violat, rights, filth, disgust, dirt, harm, delay, hurt, error, threat, injur, burn, complica, Suicide, Kill, cut, overdose, gun, knife, weapon, violence, dead, attorney, sever, shoot, threat, expose, privates, touched, accident, adverse, agon, cops, court, danger, died, grie, incident, law, liable, litigat, mal, police, priva, sue, suffer, call, infect, cruel, Fraud, hostile & investigat" Some of the words are purposely misspelled since we grabbed the word(s), prefix to make sure we captured all versions. Patients' comments were screened in real-time with the algorithm and if identified to contain any of the Hot Word, will generate an alert to the corresponding grievance coordinator. The grievance coordinator was responsible for contacting the patient and making sure that their concern was resolved and further reporting the issue on a learning tool so that the organization can learn from any safety incidents and create a reliable, safe, and effective model of care for patients.

Sentiment Analysis in this NLP study dissected textual comments, classified sentiments, and provided valuable sentiment-related metrics. This approach, complemented by the Sentiment Classification Tool, enabled a thorough exploration of patient and provider sentiments, offering actionable insights for healthcare professionals and organizations to enhance patient experiences and service quality.

RESULTS

Overall, about 18,700 patient feedback comments were run through the NPL model's sentiment analysis. The model inferred that 34.5% comments were positive, 12.9% comments (i.e., 2,405 were neutral) and 52.6% comments were positive. Thus, majority of the patients at healthcare settings were positive or neutral about their healthcare experience.

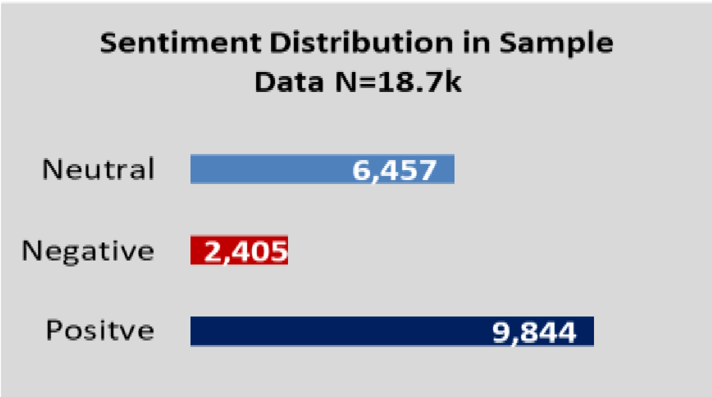

Figure 6: Sentiment analysis output on sample data.

An Aggregate analysis was performed on the data to generate a list of top words/nouns/bigrams and used to identify "words" of interest. The words of the interest were put in the categories (as shown in Figure 7 below).

```
# Create keyword list
Access = ['account', 'signing', 'sign', 'username','password', 'passwords', 'logins', 'login', 'access',
          'activation', 'user', 'user id', 'log', 'sighin', 'card', 'id', 'accounts', 'mail', 'reset',
          'logging', 'social security', 'security number', 'app', 'user friendly','pass word']
Appointment = ['appointment','scheduling','scheduled','appt','schedule','rescheduled','appointments','appoints']
Drug = ['drug','drugs']
Customer_care = ['care','customer service','customer','satisfied','caring']
Health_patient=['health','patient','medical','patients','medicine','medicines','medication']
Information = ['information','phone','email','gmaail','gmail','message','info','emails','form','forms',
               'documents','document']
Covid = ['covid', 'vaccine', 'vaccination', 'dose', 'shot', 'vaccinations']
Terms = ['terms']
Bill = ['payment', 'bill','Bill','pay','charged']
Prescription = ['prescription','prescriptions','Prescription','Prescriptions']
App = ['chart','Chart','website','web','websites','view','system','site','saved','data','code','cursor','entered',
       'enter','real time','entries','unresponsive','functional','on line','upload','dashboard']
test_results = ['test','results','lab','labs','Lab','Labs','tests','Test']
Insurance = ['Insurance','insurance']
Doctor = ['Doctor','doctor','Dr','dr','Clinician','clinician','Clinicians','clinicians','Dr.','dr.']
```

Figure 7: Keywords categorization process.

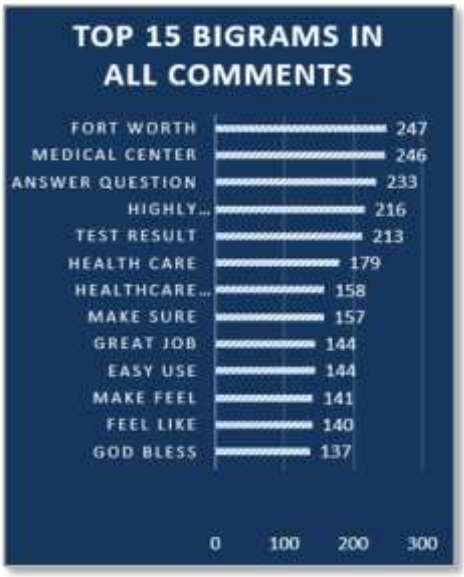

Figure 8: Bigram results from the study showing the top keywords.

Around 22.3% of the comments were related to access/log in issues as shown in Table 1 below. Performing sentiment analysis per category revealed that 78% of all Access/Log in related comments were of negative sentiment. The analysis helped revealed the access/log was a primary dissatisfier and is a top performance improvement opportunity. The average sentiment was then tracked over time for access/log in category, and a downward trend was identified. The average sentiment for Access/Log in decreased about 33.3% in four years. Top 10 Bigram for negative sentiment showed, that most patients was upset regarding activation code during log-in.

Category	No of Comments
Appointment	2,780
Access/ Log in	4,167
Bill	276
Information	121
Prescription/Drug/ Medication	109
Test Results	213
Insurance	423
Doctor/ Nurse/ Staff	2800
App	415
Covid	1,029
Others	6,267

Table 1: Top categories identified in the study. 22.3% of the comments were identified talking about Access/LogIn issues according to the NLP study.

Figure 9: line chart showing decline of patient sentiment in relation to Access/Log In features of health service portal. The study enables the healthcare system to understand long term insights such as these and implement actionable workstreams to improve patient experience.

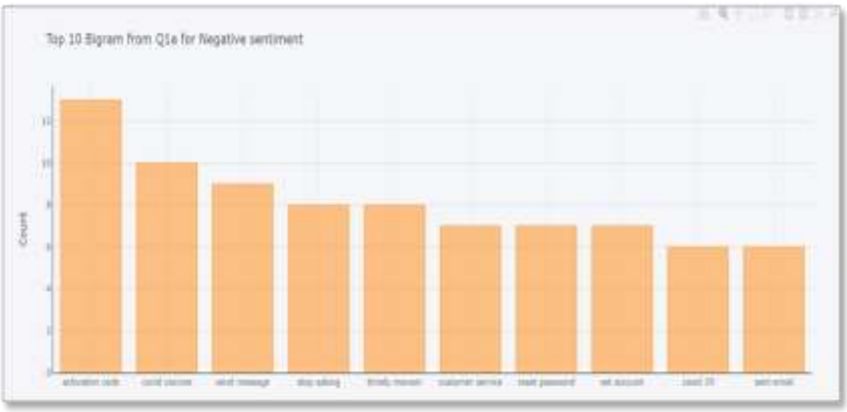

Figure 10: Top 10 categories with negative sentiment.

Furthermore, Word2Vec was trained using the collected patient data to identify word associations. It uses neural network to learn word associations from a corpus of text.

Positive word associations were found when patients used the word staff, care, and doctor. However, negative words were related to categories of website, insurance, appointment.

Word2Vec Results:

1. Staff - amazing, professional, friendly, thank, awesome, job, excellent, great, wonderful, steller
2. Care - professional, excellent, oeller, kaylah, zacharri, polyak, giver, hero, support, dedicated
3. Website - push, impossible, course, slow, forget, reset, frustrated, sanitizer, water, bathroom
4. Doctor - work, ever, miss, happy, hard, guy, sweet, experience, prayer, barksdale
5. Insurance - bill, incorrectly, copay, code, pay, fee, recorded, information, ultrasound, charge

Fig. 11 below reveals that “allow, help, time, doctor, phone, system, health, care” are the most frequent words in positive patient comments. Interestingly, there are similar words that also appear with the highest frequency in the negative comments such as “time, doctor, my chart, message” (Fig. 12).

Word Cloud Output: The larger the word, the more frequent it appeared in the comments.

Figure 11: Positive Sentiment Word Cloud.

Figure 12: Negative Sentiment Word Cloud.

Q1a Wordcloud for Positive Sentiment

```
# WordCloud for Positive wordcloud
df_pos_jj = df_jj[df_jj['Sentiment_class']=='positive']
allWords = ' '.join([word for word in df_pos_jj['Q1a_cleaned']])
word_cloud = WordCloud(width = 500, height=300, random_state= 21, max_font_size=110, background_color='white',
                       color_func=blue_color_func).generate(allWords)

plt.figure(figsize=(10,8))
plt.imshow(word_cloud, interpolation= 'bilinear')
plt.axis('off')
plt.show()
```

Figure 13: Code for calculating and implementing the output for a word cloud in the study.

Around 3.2% of the comments were identified that contained “Hot Word” list. 580 of those comments were critical to patient safety and needed immediate attention. However, there was no real-time NLP monitoring of patient comments. This clearly demonstrates the need for automation and identification of comments.

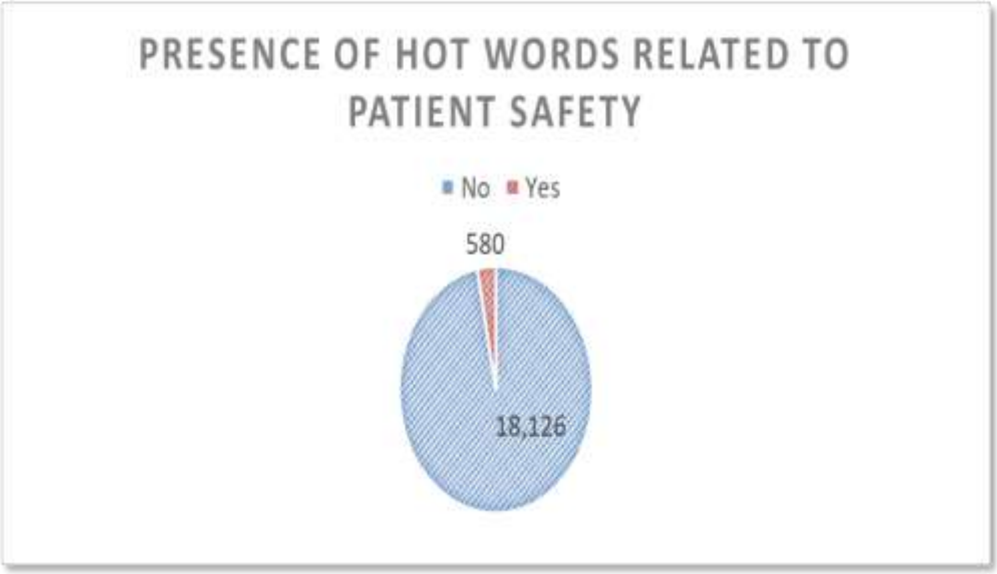

Figure 14: Hot Words can be utilized to identify sentiment around critical parameters. This figure shows comments with Hot Words around 'patient safety'. This helped healthcare system narrow down the focus on those particular comments.

Limitations

Utilizing Natural Language Processing (NLP) for deep learning in patient experience analysis has its constraints. To glean meaningful insights, thorough data preprocessing is crucial. Computers struggle to differentiate between words like "doctor" and "physician" despite their identical meanings. Similarly, "meal" and "meals" convey the same information but are treated as distinct words by computers. This issue extends to spelling errors, where a single letter replacement can result in a completely different word. Employing techniques like stemming or lemmatization resolves this by reducing words to their base form or a common standard. NLP libraries can also rectify spelling errors. A one-time manual analysis of comments can identify context-specific words, subsequently replaced by more general terms. The preprocessing complexity escalates for patient-derived data, given potential healthcare literacy gaps, spelling mistakes, and the use of informal text language not always covered by NLP libraries [4].

Utilizing frequency distribution of words or word combinations yields valuable insights. However, comprehending the context of these terms, particularly for isolated words, can be challenging when examining tables. Thus, while numeric tables provide useful summaries, understanding context often necessitates reviewing the actual feedback. These tables remain valuable in highlighting frequently appearing words, offering guidance for optimizing the use of patient feedback.

In cases involving limited data, NLP may not yield expedient results. Techniques like frequency distributions, bigrams, and trigrams rely on repetitive terms, which may not be sufficiently present in smaller comment datasets. Conversely, NLP excels with large datasets, providing sophisticated tools for analysis. By identifying patterns, NLP processes guide investigators and pinpoint comments with greater informational value, thereby reducing the need for extensive manual analysis.

Patient and client feedback data volume is on the rise, evident from the multitude of questionnaires, third-party surveys, and online reviews accessible to the public. Understanding this data is pivotal for devising interventions to enhance patient experience, intensifying the demand for efficient feedback comprehension. This is where NLP shines, efficiently processing vast data volumes. Combining NLP with machine learning empowers models to classify comments into specific categories, disentangle mixed comments for better insights, and discern words with nuanced meanings used in similar contexts. Leveraging context-aware algorithms like BERT enhances classification accuracy and equips healthcare organizations to effectively navigate the deluge of data volume, velocity, and variety they face.

LITERATURE REVIEW

There have been a few other NLP studies done across the world on free text comments from healthcare patients. Understanding the learnings from those studies and comparing the recommendations from the respective authors also is key to understanding long-term potential of implementing NLP based analysis approaches for more effective process implementation in US healthcare systems.

Study on surveys from Pennsylvania Department of Patient Experience

In this study, the researchers explored the application of Natural Language Processing (NLP) methods to analyze patient feedback data collected by Press Ganey methodology, a survey-based system designed to measure patient satisfaction with healthcare services [4]. The study aimed to gain insights into the patient experience, understand factors contributing to positive and negative feedback, and identify areas for improvement in healthcare services. The authors emphasized the challenges of analyzing patient feedback, particularly when dealing with large datasets and the complexities of natural language. They pointed out the limitations of manual analysis and the need for more efficient methods, leading to the adoption of NLP algorithms.

Data preprocessing was identified as a critical step, involving tasks like text standardization, stemming, lemmatization, and stop word elimination to prepare the textual data for analysis. The study utilized NLP techniques to classify patient comments by sentiment (positive, negative, neutral, or mixed) and extract meaningful insights. Sentiment analysis was performed on patient comments, helping identify the emotions expressed in the feedback. Word2Vec analysis was used to discover associations between words, while hot word detection helped flag comments requiring immediate attention.

The researchers applied deep learning methods, specifically a neural network-based model, to classify mixed sentiment comments into positive, negative, or neutral categories. This approach improved the understanding of mixed comments, which often contain valuable information.

The study revealed that patient feedback primarily centered on the roles of nurses and doctors in shaping the patient experience. Negative comments frequently revolved around issues related to the patient's stay, encompassing concerns about climate control, room size, and noise levels. Negative feedback also extended to tests and treatments, with mention of problems related to blood draws, IV procedures, and discharge delays. By utilizing NLP and deep learning, the researchers successfully classified mixed sentiment comments, offering insights into the specific care aspects contributing to mixed feedback. Overall, NLP techniques provided an efficient means to analyze patient feedback, enabling the identification of trends and patterns within extensive datasets. The study's limitations included the need for extensive data preprocessing and the potential for context misinterpretation by NLP algorithms. The authors also noted that manual review of comments was still necessary to fully understand context and nuances in the feedback.

This study based on the data from Pennsylvania Patient Experience department demonstrated the effectiveness of NLP methods in analyzing patient feedback data to gain valuable insights into the patient experience. By leveraging NLP, healthcare organizations can efficiently process and interpret large volumes of patient comments, identify areas for improvement, and ultimately enhance the quality of care provided.

NLP study on free text comments from NHS (London) surveys

This study aimed to leverage Natural Language Processing (NLP) and Machine Learning (ML) techniques to extract insights from the free-text comments provided by patients in response to the Friends and Family Test (FFT) survey within a large London NHS Trust [5]. The FFT has generated a vast amount of feedback data, and this study sought to systematically analyze the unstructured comments to gain meaningful information for quality improvement.

The study began by highlighting the importance of understanding patient experiences in healthcare for improving care delivery. The FFT, which includes free-text comments, was identified as a valuable resource for gathering patient feedback. However, the analysis of these comments has traditionally been resource-intensive due to the lack of systematic methods for extracting insights.

The study explored the application of NLP and ML to analyze the FFT free-text comments. It employed a deductive qualitative content analysis approach to manually code comments into themes related to patient experiences, including transitions and continuity.

The ML approach involved pre-processing the data by standardizing the text, removing stop words and punctuations, and then using supervised learning to classify comments into specific themes. Several ML models were applied, with the Support Vector Machine (SVM) achieving the highest accuracy in categorizing comments.

Sentiment analysis was also employed to classify comments as positive, negative, or neutral. The study found substantial agreement among annotators in categorizing comments according to themes and sentiment.

Word clouds and tri-grams were generated to visually represent the most frequent terms and word combinations within the comments, offering a deeper understanding of patient concerns and experiences related to transitions of care. The word clouds illustrated key terms specific to different healthcare settings, reflecting variations in patient experiences.

The study yielded valuable insights into patient experiences during transitions of care and continuity. It highlighted areas of concern, such as communication issues, appointment scheduling, and discharge processes, as identified through the analysis of tri-grams and sentiment.

The results demonstrated that NLP can efficiently process and analyze large datasets of patient feedback, providing a foundation for targeted quality improvement efforts. By identifying patterns and trends, NLP facilitates the rapid identification of issues that require attention, enabling healthcare providers to respond more effectively to patient concerns.

However, the study also acknowledged limitations, such as the focus on data from a single hospital. Generalizability could be improved by including data from multiple hospitals. Additionally, further refinement of preprocessing methods could enhance the analysis, especially for comments with short character counts.

In conclusion, this study showcased the potential of NLP and ML techniques to extract meaningful insights from free-text patient feedback data, particularly within the context of transitions of care and continuity. This approach offers a more efficient and systematic means of analyzing patient experiences and can inform targeted quality improvement efforts in healthcare settings.

CONCLUSION

Through the application of Natural Language Processing (NLP), we successfully pinpointed various concerns associated with care transitions and continuity within the unstructured free-text data of FFT (Free-Form Text) efficiently, eliminating the need for laborious manual review of all feedback. Notable issues, such as insufficient information provision and suboptimal discharge procedures, have been identified. These findings offer valuable guidance for enhancing the processes related to care transitions and continuity, utilizing a quality improvement framework.

Our recommendation is for healthcare services to leverage these NLP tools actively. By harnessing the insights derived from unstructured patient experience feedback, healthcare providers can swiftly and effectively inform care delivery improvements. This proactive approach ensures that patient feedback contributes directly to enhancing the quality of care, promoting timely interventions, and ultimately leading to better patient experiences.

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