2023-05-01

Evaluation Of Maternal Patient Experience During Covid-19 Using Natural Language Processing

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EVALUATION OF MATERNAL PATIENT EXPERIENCE DURING COVID-19

USING NATURAL LANGUAGE PROCESSING

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by

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THESIS

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

DEPARTMENT OF INDUSTRIAL, MANUFACTURING & SYSTEMS ENGINEERING

THE UNIVERSITY OF TEXAS AT EL PASO

May 2023

Acknowledgements

I am humbly grateful to my academic advisors for their invaluable guidance and support throughout my academic journey. Their expertise and encouragement have played a crucial role in shaping my perspective and enhancing my skills.

I would also like to express my heartfelt appreciation to my parents, for their unwavering love, support, and sacrifices. Their constant motivation and encouragement have been a driving force behind my accomplishments, and I owe all my achievements to their tireless efforts and dedication.

I humbly acknowledge that without their assistance, I would not have been able to achieve my academic and personal goals. I feel truly fortunate to have such wonderful people in my life, and I will forever be grateful for their contributions to my success.

Abstract

Healthcare policymakers are constantly investigating how to improve this situation and provide a more patient-centered care. Delivering excellent medical care involves ensuring that patients have a positive experience. Most healthcare organizations use patient survey feedback, like HCAHPS, to measure their patients' experiences. The United States has the highest maternal mortality or morbidity rate of the developed countries, so we used maternal patients as the patient cohort to evaluate various touchpoints. The power of social media can be harnessed to provide researchers with valuable insights into understanding patient's experience and care. We used the "COVID-19Tweets" Dataset, which has over twenty-eight million tweets, to evaluate patient experience using Natural Language Processing (NLP) and extract tweets from the US with words relevant to maternal patients. This research's objective is to develop a model to evaluate the patient experience during the COVID-19 pandemic. We created word clouds, word clustering, frequency analysis, and network analysis of words that relate to “pains” and “gains” expressed through social media regarding the maternal patient experience. This model will help process improvement experts without domain expertise to efficiently understand various challenges in the domain. Such insights can help decision-makers improve the patient care system. Additionally, the model will also discover if there is any racial health inequity faced by any particular group. Artificial Intelligence can be used to get information from social media about how patients feel. This allows healthcare organizations to be more patient centered.

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Chapter 1: Introduction

In this 21st century, a huge amount of unstructured data regarding patients' healthcare experiences is present on social media, usually posted by patients or by their family members(Greaves et al., 2013). However, this information is not captured and utilized to improve the patients' healthcare system because of the ingrained complexity in processing and analyzing this data. Text analytics comes into play to harness meaningful insights from social media the policymakers can get directions to improve and make more patient-centric care. Patients are playing a more active role in decision-making Patient-centered care, also known as person-centered care, is a healthcare approach that prioritizes the needs, values, and preferences of the patient. This approach recognizes that patients are the key decision-makers in their care and aims to involve them in the process as much as possible. As a result, the trend towards patient-centered care has been emphasized, as patients seek a more engaged experience with the use of health monitoring devices and a trusted relationship with their healthcare provider (ElKefi & Asan, 2021; Greaves et al., 2013; Ittoo & van den Bosch, 2016; P. Kumar et al., 2021; Nawab et al., 2020; Peters et al., 2020)

Patient-centered care is defined by The Institute of Medicine (IOM) as offering treatment that considers and responds to the unique preferences, requirements, and values of each patient, and making sure that the patient's values direct all clinical judgments (Wolfe, 2001). A total of six goals are suggested by the organization, which are: safe, effective, patient-centered, timely, efficient and equitable (Wolfe, 2001). Research has shown that patient-centered care results in improved patient satisfaction and outcomes, as well as better communication and collaboration between patients and healthcare providers (Wolf et al., 2008).

Patients’ experience is a highly important quality index. The outcome of a patient and the experience is strongly correlated, which means better outcomes yield better experience (Black et al., 2014). The aim of this study is to incorporate Natural Language Processing (NLP) to efficiently capture maternal patient experience from a large-scale dataset collected from Twitter. Authors selected maternal health as one of the cohorts to analyze the use of NLP to measure patient experience. Moreover, maternal health is a critical aspect of women's health and well-being, particularly in the United States (US), where maternal mortality rates are high. According to the Centers for Disease Control and Prevention (CDC), approximately 700 women die each year in the US due to pregnancy-related causes, and 60% of these deaths are preventable (Dyer, 2019). Authors attempt to analyze tweets to discover topics related to maternal health and their sentiments to understand the pains and gains expressed by the patients or their relatives or friends. Authors used IEEE coronavirus covid-19 tweets dataset for our analysis (Lamsal, n.d.). Authors also looked the data within the healthcare disparity lens to find topics related to pregnancy, maternal care, and covid-19.

Chapter 2: Literature Review

Over the past decade, there has been a significant advancement in evaluating patients' experiences which demonstrates the value of incorporating the patients' insights and demands into the healthcare system (Coulter et al., 2009; S. of S. for Health, 2008). Since the healthcare industry is becoming more and more patient-centric, it becomes a point of interest to quantify, record and improve the experience of patients under their care (Bretthauer & Savin, 2018; Esmaeilzadeh et al., 2021). A literature review was conducted to understand how patients' experience was captured, as well as the tools and techniques that garner the patients' experience. Additionally, in this section, studies were discussed which focused on Natural Language Processing (NLP): Text Analytics, specifically focused on topic modeling and sentiment analysis. Furthermore, how patients utilize social media, especially Twitter, to share their experiences is also emphasized.

2.1 Research in Patient Experience

Patients' experiences of the care and the feedback extracted from patients about those experiences are integrated to conceptualize patient experience, which is one of the most widely used terms in healthcare research. The concept of incorporating patients' experiences to improve the healthcare system dates back to the 1980s (Press PhD, 2014). They showed that evaluating the patients' nonclinical needs can not only improve care but also reduce malpractice claims. The concept started to gain a lot of attention and was a widely debated topic among policymakers. In 2002, the federal government stepped in and developed a survey named Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) with Medicare and Medicaid Services (CMS) and the Agency for Healthcare and Research Quality (AHRQ) (Nawab et al., 2020; Wei et al., 2020) to assess the patient satisfaction metric. Both cognitive and emotions should be considered as the emotional aspect is directly related to patients' satisfaction and ultimately the clinical outcome (Dube & Menon, 1998; Hermann et al., 2016; Steine et al., 2001; Vinagre & Neves, 2008). Again, if there is a lack of patient-centered care, it will result in unmet patient needs, waste of resources and ineffective care (Weiss et al., 2010).

Schuttner et al., (2020) found that patient-centered care was associated with improved patient outcomes, including improved quality of life (Sum et al., 2021). Hughes et al., (2018) showed that patients those who were involved in decision-making regarding their care reported higher levels of satisfaction and engagement with their healthcare provider. Patient-centered care also involves the use of technology and digital innovations to improve patient engagement and experience (Boissy, 2020; Moro Visconti & Martiniello, 2019). For example, the use of Artificial Intelligence (AI) to evaluate the patient experience from a large database is one of the ways to extract actionable insights to improve healthcare quality (Abualigah et al., 2020; Annapurani et al., n.d.; LaVela & Gallan, 2014; Rastegar-Mojarad et al., 2015).

Although some studies concentrate on evaluating the patient experience, only a handful of them demonstrate concrete approaches. For instance, the National Health Service (NHS) declared eight highly significant aspects for 'good' patient experience including communication, physical comfort, emotional support during distress and access to care (D. of Health, 2012). However, one of the renowned healthcare analysts, Dr. Foster Intelligence defined patient experience as ‘‘feedback from patients on ‘what actually happened’ during receiving care or treatment, both the objective facts and their subjective views of it’’ (Ahmed et al., 2014). Thus, patient experience relies on both what happened with the patient and the way the patient shared the experience. This also provides a spotlight on the subtle difference between 'patient experience' and 'patient satisfaction' which are often used interchangeably. Authors have defined satisfaction as a multidimensional, typically, not well-defined concept which relies on the subjective experience of the patients (Sitzia & Wood, 1997). This is often impacted by patient's expectations and preferences in different patient groups (Jackson et al., 2001; Staniszewska & Ahmed, 1999).

Patient satisfaction is one of the key factors widely accounted for in evaluating patients' experience. However, there are some drawbacks in terms of the tools used to assess these experiences (Sofaer & Firminger, 2005). Sometimes patient experience and patient satisfaction are used interchangeably which is wrong according to Crow and others (Crow et al., 2002). According to them, it is either satisfaction does not imply superior care, but only acceptable one, and satisfaction is relative. As a result, it is crucial to distinguish between patient experience and satisfaction. Both cognitive and emotional domains of patient experience must be accounted for (Redelmeier et al., 1993; Vinagre & Neves, 2008).

Studies have also shown that patient experience goes hand in hand with important financial indicators (Cochrane et al., 2015; T. H. Lee, 2015). For instance, superior patient experience results in lower medical malpractice which also improves the effectiveness of care, lower turnover and higher employee satisfaction (Beckman et al., 1994; Bilimoria et al., 2017; Charmel & Frampton, 2008). In addition to that, if healthcare facilities provide quality healthcare, which in turn results in better relationships with doctors and nurses, then patients tend to stick with their care provider (Safran et al., 2001).

2.1.1 Important Aspects of Patient Experience

Numerous healthcare organizations have undertaken patient-centeredness as part of their mission and strategy when IOM announced patient-centered care as one of its six objectives for improving healthcare (Collins et al., 2007). In one of the studies, Picker Institute and the

Commonwealth Fund announced eight aspects of patient-centered care of which other authors are also consistent (Genteis et al., 2003). Firstly, healthcare providers should show respect for patients' values, choices, and expressed demands, including involving patients in decision-making and ensuring that treatments align with their values (Davis et al., 2005; Meyer, 2019; Selwood et al., 2017). Secondly, integration and coordination of care are critical to providing patient-centered communication across various healthcare facilities, services, and support systems (Armanasco et al., 2012; Davis et al., 2005; Väre et al., 2016; Zinckernagel et al., 2017). Thirdly, patients should receive adequate information and education about their clinical status, prognosis, and progress throughout their journey (Davis et al., 2005; Deacon, 2012; Gualandi et al., 2019; Mahé et al., 2020; Schildmeijer et al., 2019; Swallmeh et al., 2018; Zinckernagel et al., 2017). Fourthly, physical comfort is crucial in providing support to patients for their daily needs, especially those experiencing physical pain and mobility difficulties (Beattie et al., 2015; Kinnear et al., 2020). Fifthly, emotional support and alleviation of fear and anxiety are essential in comforting patients during their journey (Deacon, 2012; Safran et al., 2001). Sixthly, involving family and friends in the patients' journey can also help provide emotional support (Gualandi et al., 2019; Zinckernagel et al., 2017). Seventhly, continuity and transition planning should ensure that patients receive ongoing treatment and services after discharge (Davis et al., 2005; Ortega, 2021; Zinckernagel et al., 2017). Finally, access to care should be easily accessible, including scheduling appointments, referral systems, and transportation (Davis et al., 2005). By integrating these components into healthcare services, healthcare providers can provide more effective and patient-centered care to meet patients' needs.

One of the important strategies to improve patient experience is to make sure the aspects that matter to patients are only measured. It can be realized that a patient's experience is an inherently personal interaction and evaluation methods cannot adequately capture the whole aspect of it only capture the reality (F. Ahmed et al., 2014). For instance, depending on the individual patients, the requirement for information is completely subjective. Although several studies have expressed the significance of information sharing and communication is one of the critical aspects of patient experience (Armanasco et al., 2012; Gualandi et al., 2019; Meyer, 2019; Wei et al., 2020; Zinckernagel et al., 2017), it varies depending on the individual. Sometimes not being able to provide information about the care might cause severe anxiety to the patient, especially in life-threatening conditions(Lazarus & Folkman, 1984). Again family members might be more concerned about the information compared to the patients (Font et al., 2018; Heaney & Hahessy, 2011).

The patient-provider relationship is another key aspect of the patient experience, since the empathy behind the care is absolutely important (Tan et al., 2017; Timmermans & Almeling, 2009). One of the studies demonstrates that interpersonal interactions with the medical staff which is authentic have positively impacted the patient experience (Kreuzer et al., 2020). The collaboration between health professionals also ensures the prescription for the treatment are accurate which results in good quality care delivered (Easton et al., 2009).

2.1.2 Approaches for Measuring Patient Experience

There are three common approaches for measuring patient experience: qualitative methods, quantitative methods, and mixed methods.

Utilizing a structured questionnaire to evaluate Patient Reported Outcomes is one of the most widely used examples of Quantitative Methods. Questionnaires are formatted in such a way that will provide numerical data to discover useful insights, patterns and trends in healthcare systems (Cappelleri et al., 2014; Regnault & Herdman, 2015). This approach is suitable for a relatively large database and also provides the ability to compare (Black et al., 2014). However, there is always an absence of patients' experiences in his/her own words. In order to recover from this challenge survey experts have shifted their attention to reports of experience (Brookes & Baker, 2022; Collett et al., 2019; Meredith & Wood, 1996).

In Qualitative methods**,** patients are allowed to express their experience in their own words which gives an in-depth understanding. By doing so better insights can be gained regarding patient observations, behavior and the meaning of their experiences. Though utilizing this method needs special training, the lack of statistical analysis and reliability makes it vulnerable to misinterpretation (Fottler et al., 1997).

Mixed methods are developed in order to acquire the full spectrum of the patient experience (LaVela & Gallan, 2014). One of the strong points of this method is the ability to cross-validate qualitative and quantitative data and find converge points.

2.2 Research in Text Analytics

The text analytics collect trends, insights, sentiment, and topics of interest using an automated process of drawing information from unstructured data and take advantage of tools, methods, and mathematical algorithms to analyze and make computers understand text, and speech (Chowdhary, 2020). It can differentiate between positive and negative emotion from the text (Hasan et al., 2019; Kanakaraj & Guddeti, 2015; Nasukawa & Yi, 2003), topics that is being discussed (Hagen et al., 2015; Sarioglu et al., 2012) and the association between the keywords. Text analytics contains a wide variety of applications such as descriptive, prescriptive, or predictive analytics (Gallagher et al., 2019; Ittoo & van den Bosch, 2016; Nam & Lee, 2019; Ranaei et al., 2019).

One of the most significant methodologies of text analytics in Natural Language Processing (NLP). NLP which is a branch of Artificial Intelligence (AI), essentially gives computers the power to understand human language: written text and spoken words, in a similar way an ordinary person would understand (Chowdhary, 2020; Hirschberg & Manning, 2015; Indurkhya & Damerau, 2010; Liddy, 2001; Nadkarni et al., 2011). Consolidating computational linguistics and machine learning, NLP gives computers the ability to process and comprehend human language. There are a series of processes that are carried out in order to disintegrate the human text in an efficient way which helps the computer to comprehend making it critical for smart healthcare (Kanakaraj & Guddeti, 2015; Singh et al., 2011; Zhou et al., 2022). Due to extensive focus from numerous researchers for the past several years, NLP has become a hot topic of research. For instance, using NLP researchers have carried out a large-scale analysis of the counseling conversation to effective counseling to the patients (Althoff et al., 2016), analyzed health insurance claims to find fraud or abuse (Popowich, 2005), assisted in assessment and rehabilitation of patients during COVID-19 pandemic, digitization and classification of the prescriptions (Carchiolo et al., 2019), structured and extracted information from patients' healthcare records (Braun et al., 2022), extracted sentiment of the patients from healthcare surveys (Abirami & Askarunisa, 2017; Abualigah et al., 2020; Clark et al., 2018; Clarke et al., 2018; Georgiou et al., 2015) and so on. All of these applications can be broken down into several categories which are sentiment analysis, speech recognition, speech tagging (use of a particular word according to context), named entity recognition, word sense disambiguation, and natural language generation.

2.2.1 Topic Modeling

Topic modeling is an effective and practical tool in Natural Language Processing for analyzing large text documents (Hagen et al., 2015; Ramage et al., 2009; Sandhiya et al., 2022). Topic modeling enables the automatic grouping of words into topics and can also identify relationships between documents within a dataset. As an example, we could consider a three-topic model of a customer feedback dataset for a retail company, including "product quality," "customer service," and "pricing." The most common words in the "product quality" topic (Topic 1) might be durability, performance, and reliability. In contrast, the "customer service" topic (Topic 2) might include words such as response time, friendliness, and helpfulness. Finally, the "pricing" topic (Topic 3) could be composed of words such as affordability, value, and discounts. Latent Dirichlet Allocation (LDA) is one of the most widely used topic modeling algorithms (Chary et al., 2019; Harrison & Sidey-Gibbons, 2021; Yibo Wang & Xu, 2018). It labels every tweet as a particular topic based on the keywords. LDA aims to find out the range of topics contained in a particular document. One of the earliest applications of LDA in topic classification was presented by Blei et al., (2003). In this paper, authors used LDA to model the topics present in a corpus of articles from the science journal Nature. They showed that LDA was able to accurately identify the topics present in the corpus and assign each article to one or more of those topics. Since then, LDA has been applied to a wide range of NLP tasks, including topic classification. For example, X. Wang & McCallum, (2006) used LDA to classify documents in the 20 Newsgroups dataset, achieving state-of-the-art performance at the time. LDA has been widely used in the medical and healthcare sector to analyze and classify various types of healthcare data. One application of LDA in healthcare is in the analysis of electronic health records (EHRs). EHRs contain a wealth of information, including clinical notes, diagnosis codes, and laboratory results, among others. LDA has been used to analyze EHRs and identify patterns in patient data, such as comorbidities, disease progression, and treatment outcomes (Li et al., 2022; Patra et al., 2021). For instance, Li et al., (2022) used LDA to identify topics related to medication use, side effects, and co-occurring conditions in EHRs. In one of the studies used LDA to analyze patient feedback from hospital surveys to identify topics and sentiments expressed by patients. The researchers found that the most frequently mentioned topics included communication, staff attitude, and overall experience (Fairie et al., 2021; Gross & Murthy, 2014). In a similar study, Hao et al., (2017) used LDA to analyze online patient reviews of healthcare providers. The researchers identified six topics related to patient experience: communication, care quality, appointment scheduling, billing, waiting time, and facility quality. The study revealed that patients placed a high value on communication and care quality, and that negative experiences with billing and waiting times were significant factors in negative reviews. These findings can be used by healthcare organizations to prioritize areas for improvement in patient experience. Another application of LDA in patient experience research is in identifying factors that influence patient satisfaction. For example, one study by Ji et al., (2019) used LDA to analyze patient feedback from a Chinese hospital to identify factors that influence patient satisfaction. The researchers found that factors such as physician communication, nursing care, and waiting time were significant predictors of patient satisfaction. Again, Ortega, (2021) utilized patient feedback from social media to find out the breast cancer patient experience. The author used LDA to find the latent topics shared by the patient and also analyzed the sentiments behind those topics. These findings can be used by healthcare organizations to prioritize areas for improvement in patient satisfaction.

In addition to identifying topics related to patient experience, LDA can also be used to analyze changes in patient experience over time. For example, one study conducted by Ao et al.,

(2020) used LDA to analyze patient feedback over a three-year period to identify changes in patient experience. The researchers found that while topics related to communication and staff attitude remained consistent over time, topics related to waiting time and access to care became more prominent in later years. These findings can be used by healthcare organizations to identify areas where patient experience has improved or declined and to develop interventions to address these changes (Ortega, 2021).

One challenge in using LDA to analyze patient experience is the need for large amounts of data. However, recent advances in electronic health record (EHR) systems and widespread use of social media have made it easier to collect and analyze patient feedback on a large scale. For example, one study by Okon et al., (2020) used LDA to analyze over 176,000 patient feedback comments from Reddit. The researchers identified topics related to dermatology patient experience, including communication, waiting times, and nursing care. These findings can be used by healthcare organizations to identify areas for improvement in patient experience. Another challenge in using LDA in patient experience research is the subjectivity of the identified topics. LDA is an unsupervised learning method, which means that the topics are identified without prior knowledge of their content (Okon et al., 2020; Pérez et al., 2018). As a result, the interpretation of the identified topics can be subjective and may require human validation. However, since social media platforms can be anonymous, there seems little incentive for patients to be dishonest.

2.2.2 Sentiment Analysis

One of the most widely used tools to garner sentiment from text or voice messages is Sentiment Analysis which classifies the underlying emotion as positive, negative and neutral (Nasukawa & Yi, 2003; Rajput, 2020). Different businesses use sentiment analysis to discern and extract subjective insights from customer reviews or opinions and based on that they improve their service (Chaturvedi et al., 2017; Jagdale et al., 2019). Sentiment analysis is widely used in clinical analysis and health informatics. It is very crucial for the healthcare systems when they analyze the sentiment of the patients regarding the care they have received and in terms of doctors and others involved in the care process can identify and resolve the problems. There are some studies that utilize the power of sentiment analysis to improve healthcare quality. For instance, by utilizing the online reviews of the consumers, decision-makers are able to take effective decisions to improve their customer experience which ultimately improves sales and also satisfaction (Awwad & Alpkocak, 2016; Clark et al., 2018; Liu, 2012). However, dealing with a huge amount of unstructured text from social media is highly computationally expensive and also takes a lot of time so authors have proposed a weighing method to analyze the sentiment and serve as a powerful decision-making tool (Abualigah et al., 2020; Chintalapudi et al., 2021; Janssen et al., 2006). Asghar et al., (2016) have analyzed possible use cases in the healthcare field and prepared a research review. Sentiment analysis can be performed at three levels: the document level, sentence level, and aspect level. The document level (Bibi, 2017) is the most common analysis that applies to the whole document. Thus, it is not suitable for precise evaluation. The Sentence Level (Marcheggiani et al., 2014) aims to evaluate a sentence's polarity, topic, or content in general. The Aspect Level analysis considers various aspects of a sentence, such as the tone, context, and emotion expressed by the sentence.to get insights such as customer opinions, identify trends, and make data-driven decisions. At first, it distinguishes the entities and the aspects and then assesses the sentiment behind different opinions for different aspects of the same entity (Tian et al., 2021; Vanaja & Belwal, 2018; Wang et al., 2019).

Different industries such as tourism, politics and marketing extensively utilize the power of sentiment analysis (Bucur, 2015; Fernández-Gavilanes et al., 2016; Gull et al., 2016). However, there are a few research in healthcare industry that explore text analytics. For instance, sentiment analysis provides decision-makers the insights regarding how patients are feeling towards caregivers, and treatment systems (Ramírez-Tinoco et al., 2019). Greaves et al., (2014) presented a mixed-method study to evaluate the patient experience and hospital quality from a small number of tweets. Hawkins et al., (2016), utilized machine learning approach to analyze data from 2349 US hospitals over one year to find out the patient's experience in various aspects such as the care they received, hospital administration and interaction with healthcare professionals. Crannell et al., (2016) presented a study where authors have analyzed emotions from tweets of various types of cancer patients with respect to unique cancer diagnostics (Crannell et al., 2016). Similarly, Rodrigues et al. have introduced a tool called SentiHealth-Cancer (SHC-pt) to identify the mental condition of cancer patients from social media (Rodrigues et al., 2016). While surveys and patient feedback are commonly used to measure patient experience, patient journey mapping can capture it more comprehensively. Ortega, (2021) utilized natural language processing algorithms to measure patient experience from social media data of breast cancer patients, which can provide valuable insights for improving empathetic and respectful care in clinical systems and enhancing patient-centered care.

Depending on the approaches there are two different types of sentiment analysis: Lexicon-based approach and machine learning-based approach which are illustrated in Figure 1. In the lexicon-based approach the terms phrases, sentimental idioms and expressions are utilized. On the other hand, in machine learning based approach usually, a computer model is trained using a dataset with defined emotions and then predictions are made (Mouthami et al., 2013).

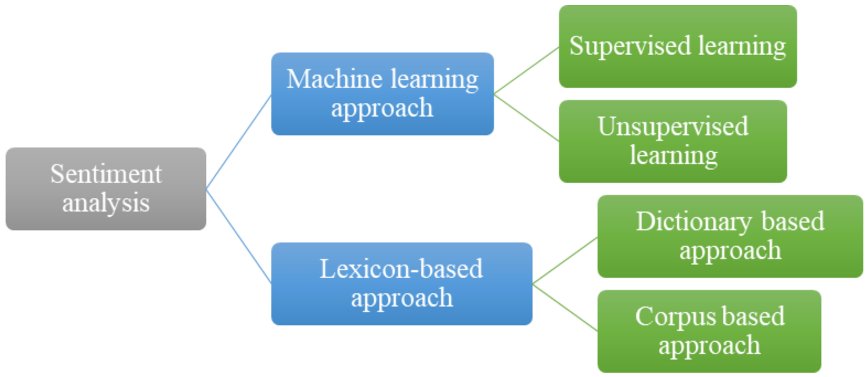

Figure 1: Sentiment Analysis Technique

One of the rule-based sentiment analysis tools that has gained significant attention in recent years due to its high accuracy and efficiency in analyzing sentiment in social media texts is VADER (Valence Aware Dictionary and sEntiment Reasoner). This tool was developed by researchers at the Georgia Institute of Technology and is specifically designed to handle social media data, which often contains informal language, slang, and abbreviated words (Hutto & Gilbert, 2014). Several studies have evaluated the performance of VADER in sentiment analysis. In a study conducted by Hutto & Gilbert, (2014), VADER was compared to other sentiment analysis tools such as TextBlob and the Stanford CoreNLP. The results showed that VADER outperformed the other tools in terms of accuracy, particularly in identifying neutral sentiment. The authors also noted that VADER was able to detect sentiment in informal language, which is often used in social media texts. Similarly, in a study by Elbagir & Yang, (2019), VADER was found to be highly effective in detecting sentiment in Twitter data. The authors compared VADER to a widely used NLTK sentiment analysis tool and found that VADER achieved higher accuracy and was more efficient in analyzing large volumes of data. In addition to its accuracy, VADER's ability to handle contextual information has also been praised. In a study by A. Kumar et al., (2020) VADER was compared to other sentiment analysis tools, including SentiStrength and AFINN, in analyzing sentiment in online product reviews. The authors found that VADER performed better than the other tools in identifying sarcasm and irony, which are often used in online product reviews. In this research, authors have used the VADER sentiment analysis to analyze maternal patient experience from Twitter.

2.3 Study Contribution

From the discussion of the relevant literatures, authors find that there is a research gap in evaluating maternal patient experience and given the adverse condition of maternal healthcare condition of USA, the cohort is country specific. In this study, the authors aim to evaluate the maternal patient experience during COVID-19 pandemic from social media. To achieve this objective, authors formulated an NLP program to discover the dominant topics patients express on Twitter and the sentiment behind this and measure patient experience.

Chapter 3: Methodology

In order to evaluate the patient's experience from Twitter, the study follows a properly defined series of steps to extract the common topics maternal patients talk about and then evaluate the sentiment behind this. At first, data preprocessing was done to make the data ready for Natural Language Processing algorithms.

In this study, Tweets were collected from an IEEE source (https://ieee-dataport.org/open-access/coronavirus-covid-19-tweets-dataset) which was collected using several COVID-19 related keywords. A subset of the dataset of 28,087,954 tweets was used in this study. These tweets are specifically from the users that posted regarding COVID-19 pandemic. Figure 2 shows a high-level overview of the study.

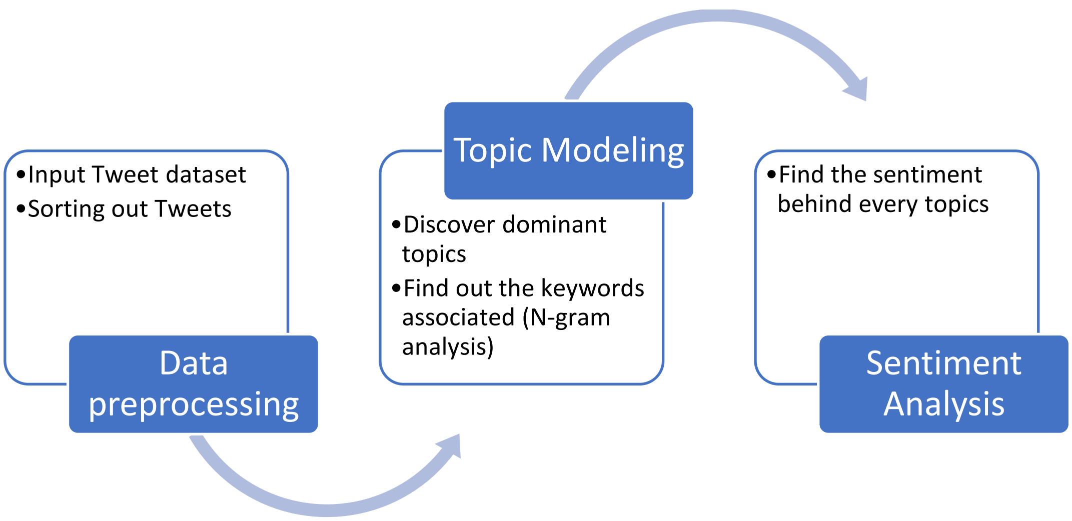

Figure 2: High-Level Overview of The Framework

3.1 Data Pre-Processing

Firstly, the tweets are preprocessed, using R programming, by filtering out the tweets posted only from the USA based on geographical location specified. Several R packages were used such as lubridate, dplyr, plyr, tidyr. Then we used several relevant keywords identified for maternal patients (Gingrey, 2020; Hoyert, 2022; Ortega, 2021; Thoma & Declercq, 2022) such as 'maternal', 'nursing', 'maternal_health', 'pregnancy', 'preeclampsia','pre-eclampsia', 'infant', 'motherhood', 'gynecology', 'postpartum', 'maternalmentalhealth', 'maternal_mortality', 'obstetrical', 'womenshealth', 'doula','obstet', 'pregnancyrelated', 'gynecology', 'cesarean', 'preterm', 'pregnancyrelated', 'gynecol', 'perinatal', 'blackmaternalhealth', 'childbirth', 'pregnant', 'mentalhealth', 'breastfeeding', 'momlife', 'birth', 'baby', 'blackmamasmatter', 'healthcare', 'newmom', 'newborn', 'fourthtrimester', 'maternalhealthmatters', 'birthworker', 'postnatal', 'postpartumjourney', 'midwife', 'maternitycare', 'midwives', 'mother', 'holisticpregnancy', 'maternal', 'breastfeedingmom', 'reclaimlabor', 'charlestonsc', 'healthypregnancy', 'educateyourself', 'reclaimbirth', 'postpartumsupport', 'informeddecisions', 'intentionalbirth', 'reclaimourbodies', 'perinatalmentalhealth', 'birthinpower', 'birthsupport', 'selfcare', 'antenatal', 'antenatal care' were used to further filter out the tweets. After this data pre-processing the final list of 31,438 tweets are merged into a CSV format for NLP algorithms.

3.2 NLP Pipeline

After the dataset was preprocessed, it was fed into the NLP pipeline. The NLP pipeline was formulated using Python 3.5 in jupyter notebook. There are several steps for the NLP which are described with a flow chart in Figure 3.s

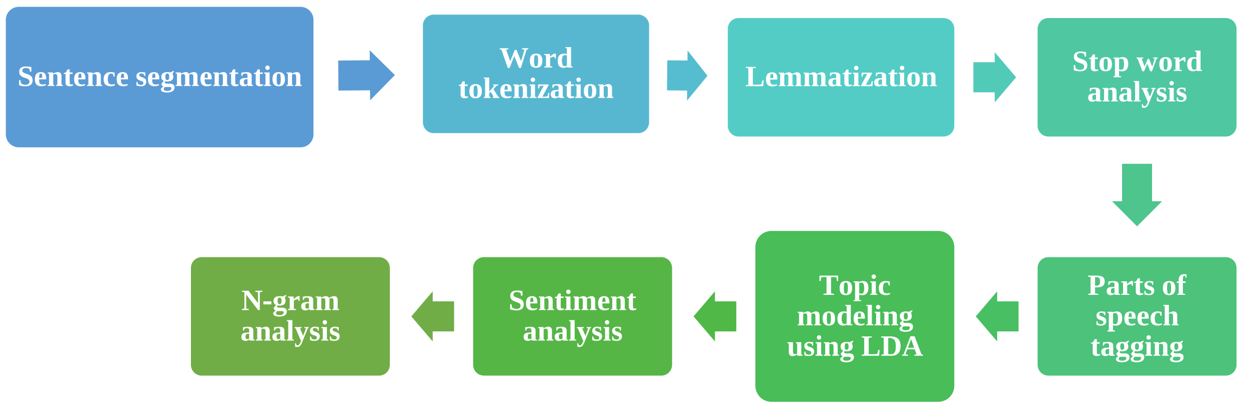

Figure 3: Flowchart of NLP pipeline

The further processing uses NLTK package to remove unnecessary stop words, emoji, and punctuations from the raw tweets that do not convey any meaning for the topic modeling. Then the words were tokenized and then using Python's NLTK library stemming, and lemmatization is done. In lemmatization, words are converted into the base form for efficient analysis. Each word was tagged with its respective parts of speech. After this step, the dataset is ready for the Topic Modeling algorithm.

3.2.1 Topic modeling

The method known as Latent Dirichlet Allocation (LDA) (Blei, 2012; Blei et al., 2003) is a technique used to represent a group of documents based on their underlying themes. Topic modeling, which is a process inherent to human knowledge, is being studied by statistical models such as LDA in the field of artificial intelligence. The aim of topic modeling is to characterize a tweet as a distribution over topics and the topics as a distribution over words. Essentially, this means that a tweet is assigned a probability for each topic, and each topic is assigned a probability for each word. In order to determine the probability of a given string, whether it be a sentence or a document, LDA calculates the likelihood of the string within the domain. Blei et al., (2003) explained the following generative process for LDA:

1. A distribution over topics is randomly selected for every tweet.
2. For every word in the tweet
    a. Randomly select a topic from a distribution over topics in first step.
    b. From the corresponding distribution over the vocabulary select a word randomly.

According to Blei et al., (2003) LDA is a statistical model that generates a corpus. Essentially, it represents tweet as a combination of random topics that are not observable, and each topic is associated with a set of words that have a probability of being used.

Select N ~ Poisson (ξ) and select θ ~ Dir (α) then for every N word ω_n : select a topic z_n ~ Multinomial (θ), select a keyword ω_n from $p(\omega_n \mid z_n, \beta)$, a multinomial probability conditioned on the topic z_n.

Step 1 is not particularly important for determining the actual topic structures. In this step, a random tweet with a certain number of words is generated based on a Poisson distribution, but it does not play a role in reversing the process. These process descriptions outline the assumption of how a corpus of tweets is created, specifically assuming a "bag of words" and topic mixture. While tweets are actually written by different users, this generative process assumption using a random θ (per-document topic distribution) and a random β (per-topic word distribution) allows for an equation to be derived that can reverse the generative process when provided with evidence (the actual corpus of tweets). The following Eq. (1) is the equation for Dirichlet Distribution derived from Blei et al., (2003)

$$p(\theta|\alpha) = \frac{\Gamma(\sum_{i=1}^{k} \alpha_i)}{\prod_{i=1}^{k} \Gamma(\alpha_i)} \theta_1^{\alpha_1 - 1} \ldots\ldots \theta_k^{\alpha_k - 1}$$

The next Eq. (2) is also derived from Blei et al., (2003) for every tweet

$$p(\theta, \boldsymbol{z}, \boldsymbol{w}|\alpha, \beta) = p(\theta|\alpha)\prod_{n=1}^{N} \mathrm{p}(\,\omega_n|z_n, \beta)$$

Here, the joint distribution of θ (the topic mixture), z (some set of topic distributions), and ω (the N words in that tweet) given α and β. Eq. (3) derived from Blei et al., (2003) which computes the probability of group of words ω present in a tweet.

$$p(\boldsymbol{w}|\alpha, \beta) = \int p(\theta|\alpha)(\prod_{n=1}^{N}\sum_{z_n} p(z_n|\theta)p(\omega_n|z_n, \beta))d\theta$$

Eq. (4) derived from Blei et al., (2003) utilizes the product of the marginal distributions of every tweet to get the Equation 4

$$p(D|\alpha, \beta) = \prod_{d=1}^{M}\int p(\theta_d|\alpha)\,(\prod_{n=1}^{N_d}\sum_{z_{dn}} p(z_{dn}|\theta_d)p(\omega_{dn}|z_{dn}, \beta))d\theta_d$$

By inputting all possible values for α and β maximize the probability of a specific corpus. The detail process of α and β hyperparameters are discussed in Blei et al., (2003) and Gross & Murthy, (2014).

LDA has several advantages, including its ability to effectively explore and clarify large document collections by narrowing them down to a specific subject area. LDA is commonly used in summarizing text and retrieving information, providing users with concise and easy-to-understand information (Chauhan & Shah, 2021; Ritter & Etzioni, 2010). Another benefit of LDA is that it can create a topic cluster, a group of words that represent a particular theme, and map the text collection to a low-dimensional topic subspace. This simplifies browsing through vast collections of text, digital libraries, web content, and other resources (Chauhan & Shah, 2021).

In this study LDA was implemented using python's genism package. The LDA algorithm uses processed tweets to identify the specified number of topics. The NLTK and genism packages of Python were utilized in this step. Now to determine the number of topics coherence score method was used by the authors (Syed & Spruit, 2018a, 2018b). In this method different values of the 'number of topics' are used in the LDA model and then a respective topic coherence score is calculated. Based on this the optimal number of topics is the 'number of topics' which have the maximum coherence value (Syed & Spruit, 2018b). In order to visualize the topics an inter-topic distribution mapping is used.

3.2.2 Sentiment Analysis

After each tweet is associated with a specific dominant topic, sentiment analysis was conducted using TextBlob and vaderSentiment package of Python. Polarity and subjectivity are the two most popular measures of sentiment analysis (Ahuja & Dubey, 2017; Cobos et al., 2019; Gujjar & Kumar, 2021) and in this study, these two measures were used. The primary objective of sentiment analysis is to categorize a specific sentence or block of text as either positive, negative, or neutral. This can be accomplished through a variety of methods, including machine learning algorithms, rule-based systems, and lexicon-based approaches. Machine learning algorithms use training data to build models that can predict the sentiment of new text data, while rule-based systems use a set of predefined rules to classify text based on specific patterns. Lexicon-based approaches use dictionaries of sentiment-laden words to classify text based on the presence or absence of specific words or phrases.

In this paper, the author has utilized VADER (Valence Aware Dictionary and sEntiment Reasoner) tool for analyzing sentiment that follows a set of rules. It is used to determine whether a text has a positive, negative, or neutral tone. The researchers at the Georgia Institute of

Technology designed VADER to work well with social media texts (Hutto & Gilbert, 2014). The tool relies on a lexicon or dictionary that includes words and phrases that are associated with sentiment scores (Elbagir & Yang, 2019). Each word is given a score that represents whether it is positive, negative, or neutral. Additionally, the lexicon includes a set of rules that adjust the sentiment scores based on the context of the words. These rules consider the presence of negation words, intensifiers, and punctuation marks. To determine the sentiment of a text using VADER, the text is first divided into individual words and punctuation marks. VADER calculates a sentiment score for each word using the lexicon, taking into account the relevant modifying rules. The sentiment scores for each word are then combined to generate an overall sentiment score for the text (Hutto & Gilbert, 2014). The overall sentiment score produced by VADER is a continuous value that ranges from -1 to 1, where -1 indicates extremely negative sentiment, 0 indicates neutral sentiment, and 1 indicates extremely positive sentiment. VADER also generates scores for each of the three sentiment categories (positive, negative, and neutral) as well as a compound score, which is a normalized weighted composite score that represents the overall sentiment of the text on a scale from -1 to 1.

Now subjectivity in sentiment analysis refers to the extent to which a text expresses personal opinions, feelings, or attitudes (Montoyo et al., 2012). It is an important aspect to consider in sentiment analysis because subjective texts often have more complex and nuanced meanings than objective ones(H. Lee et al., 2013; Montoyo et al., 2012). For instance, a positive review of a restaurant may contain various subjective expressions such as "the food was amazing," "the ambiance was fantastic," or "the service was outstanding." There are different approaches to detect subjectivity in sentiment analysis. One common approach is to use lexicons or dictionaries that contain words with positive or negative connotations. This method involves assigning a sentiment score to each word in the text based on its polarity, and then combining these scores to obtain an overall sentiment score for the text. Another approach is to use machine learning algorithms, such as support vector machines or neural networks, that are trained on a dataset of annotated texts to predict the sentiment of new texts. In this study the author has utilized the lexicon-based approach to quantify subjectivity of every tweet using python's TextBlob package. After the sentiment analysis the final output contains every tweet classified into a topic along with the sentiment behind that topic.

3.2.3 N-gram Analysis

After the sentiment analysis, the N-gram analysis was conducted for every topic depending on the polarity. N-gram analysis is a text mining technique that is used to analyze the structure and content of written language (H. Ahmed et al., 2017; Lavanya & Sasikala, 2021; Sidorov et al., 2014). An N-gram is a contiguous sequence of n items from a given sample of text, where n is an integer that represents the number of items in the sequence (Sidorov et al., 2014). In N-gram analysis, the sample text is divided into N-grams, which are then counted and analyzed to determine their frequency and distribution. The most common form of N-gram analysis is the bigram (n=2), which considers pairs of adjacent words in the text. This type of analysis is useful for identifying patterns and relationships between words in the text, such as common collocations or idiomatic expressions. Trigram (n=3) analysis considers three adjacent words, and higher-order N-grams consider even more words. N-gram analysis is widely used in various applications, such as natural language processing, information retrieval, and machine learning. For instance, it can be used to identify the most frequently occurring words in a given text, to identify patterns in the usage of certain words or phrases, or to develop language models that can predict the next word in a sentence based on the preceding N-grams.

Chapter 4: Results

At the first stage of data preprocessing from 28 million tweets, around 31,438 tweets were extracted that talk about maternal healthcare and from the USA. After the stop word removal and lemmatization, the processed tweets were transferred to the next step which is topic modeling.

Now from the LDA topic evaluation by using different values of 'number of topics' authors find the optimal number of topics which is 3. The LDA model coherence values are shown in below Figure 4. In this figure we can see that for number of topics 3 the model generates maximum coherence score which is 0.3466 and after that as the number of topics increases the coherence score decreases.

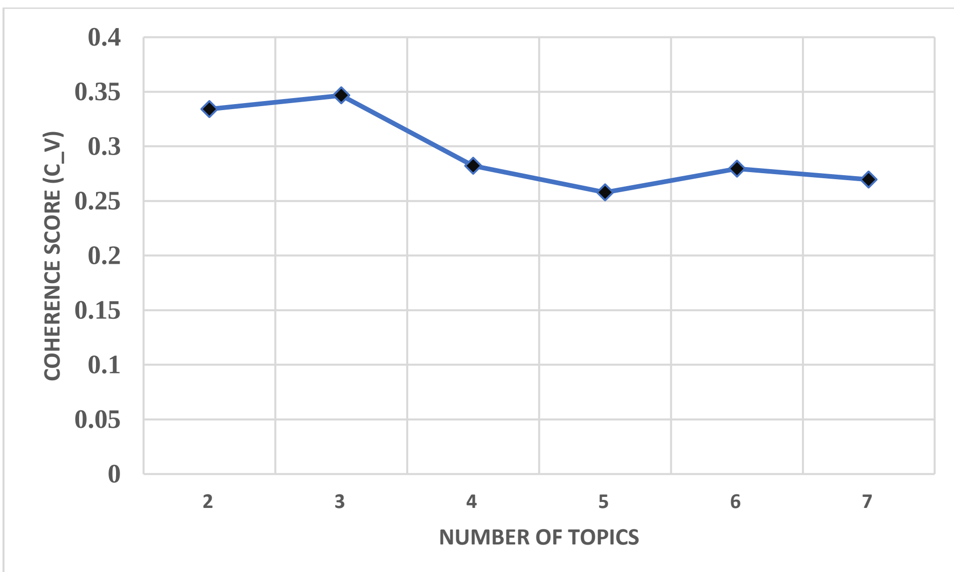

Figure 4: Coherence score of LDA model for different number of topics

Thus the number of topics for the LDA model was set to three and theses three topics are visualized in different ways. At first, a word cloud was drawn for every topic depicted in Figure 5. The keywords inside these word clouds represent each topic.

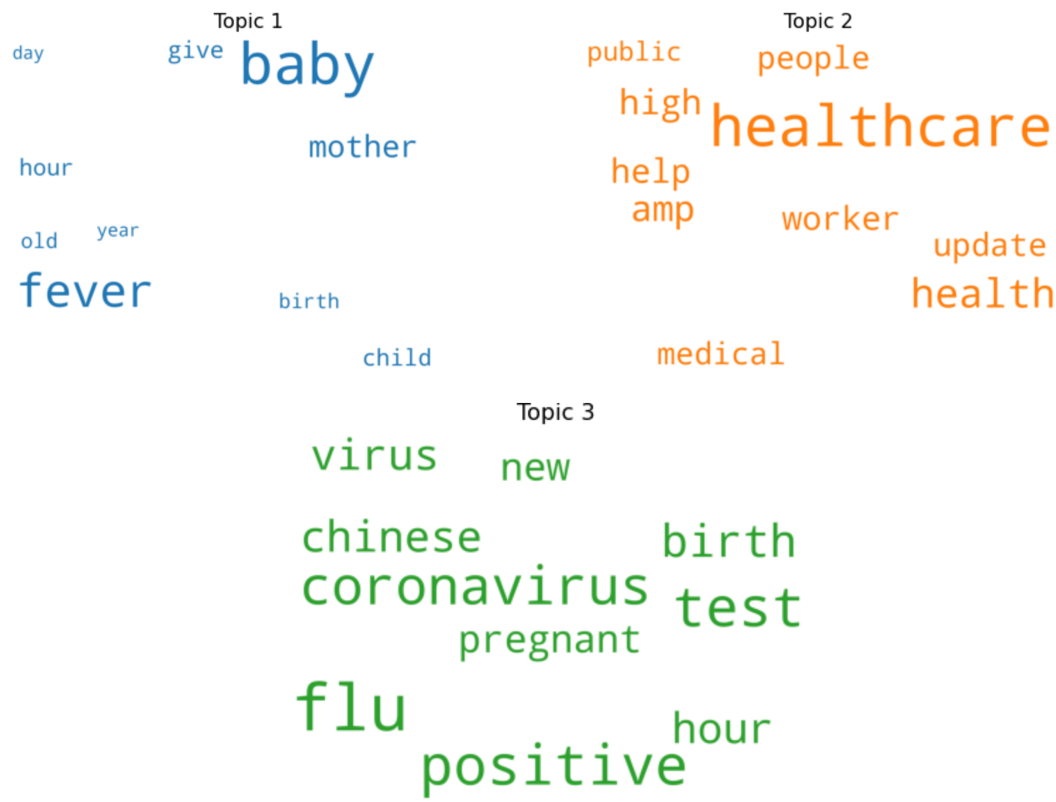

Figure 5: Word cloud of 3 topics

Now the frequency of the most represented keywords in each topic is depicted in the following bar charts in Figure 6. It is evident that in Topic 1fever, baby, mother, birth is most frequent. In contrast, Topic 2 has healthcare, high, help, worker, public, health medical, are most frequent. In topic 3 coronavirus, positive, flu, birth, pregnant, test are most frequent.

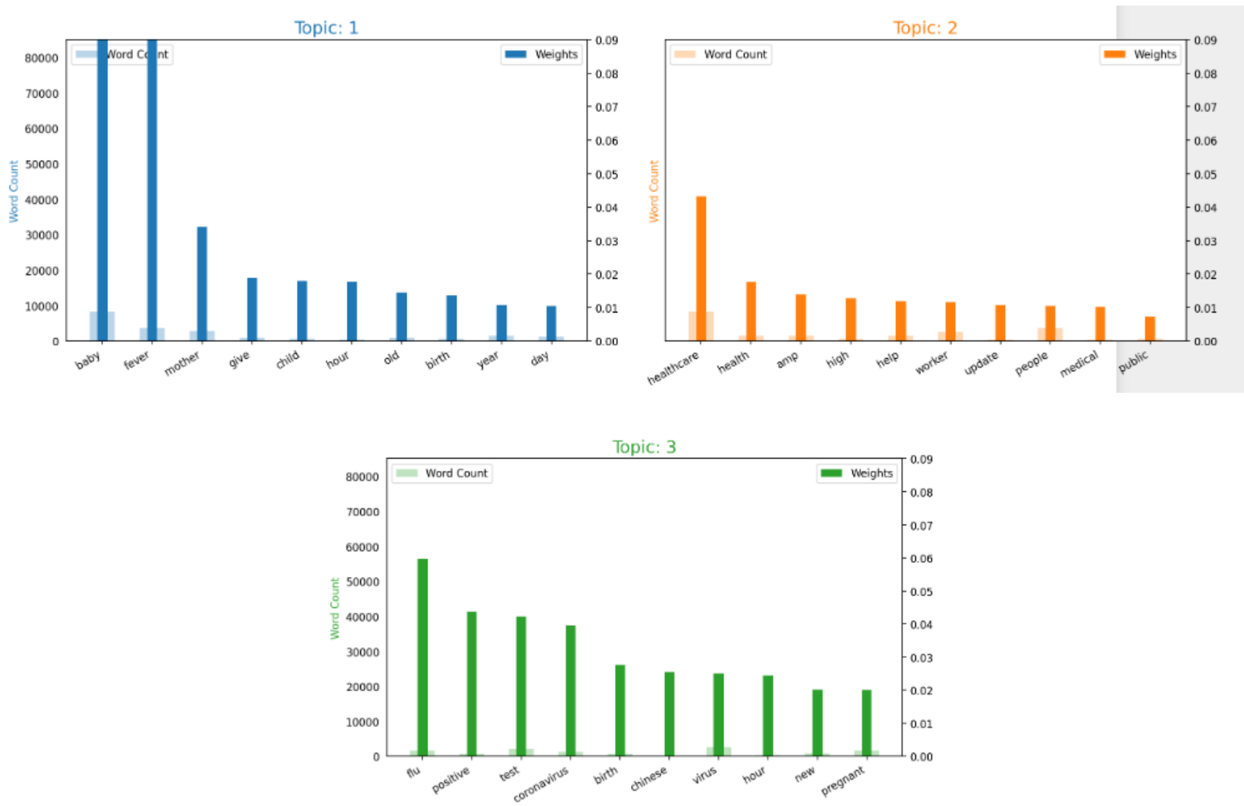

Figure 6: Word count and importance of topic keywords for each topic

From the above analysis, labels can be assigned to every topic. Depending on the keyword frequency in Topic 1 users talking about pregnant mothers and newborn baby's mother worried about flu, in Topic 2 impact on healthcare facilities and consequences on pregnant mothers andin Topic 3 tweets are concerned about the rising flu which could be coronavirus positive cases, COVID-19 testing and rapidly spreading virus and effect on pregnant mothers.

Depending on these keyword frequencies, every tweet is classified into different topics which are shown in three different colors in Figure 7. Here orange, green and blue colored tweets represent three different topics based on the keywords they have.

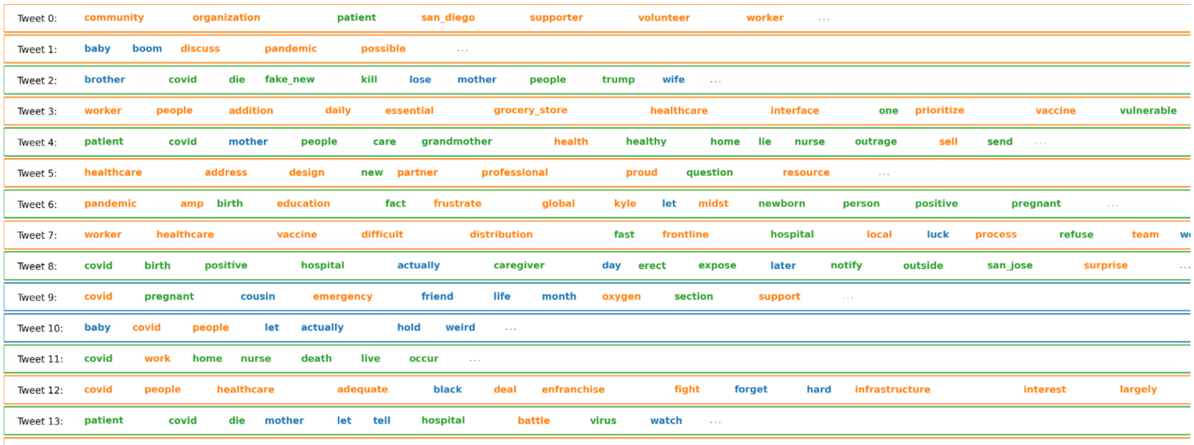

Figure 7: Tweets classified into topics

Then, the distribution of each topic in the dataset is shown in Figure 8. Here it is evident that the majority of the tweets fall under topic 2 and topic 1.

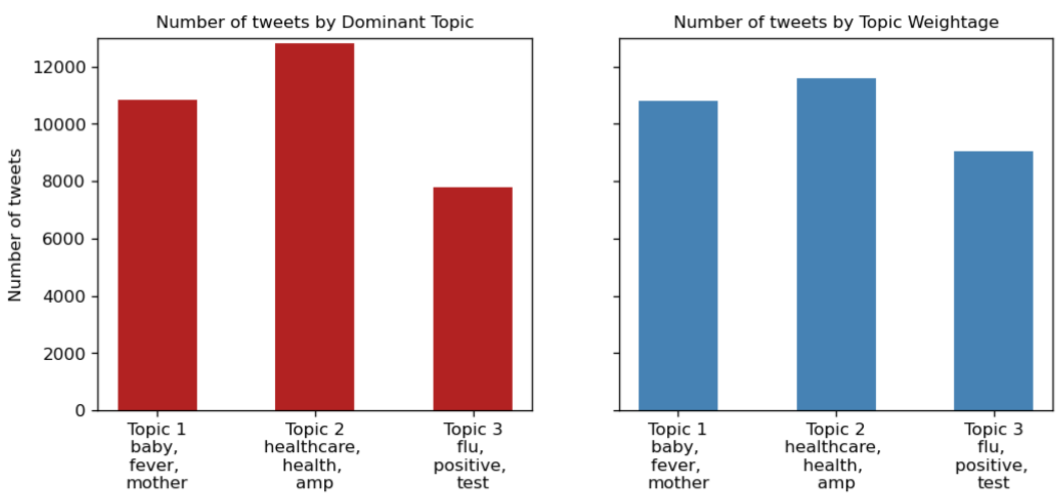

Figure 8: Distribution of topics

Furthermore, all the dominant topics were shown in an inter-topic distance map to better visualize how topics are classified. This is illustrated in Figure 9.

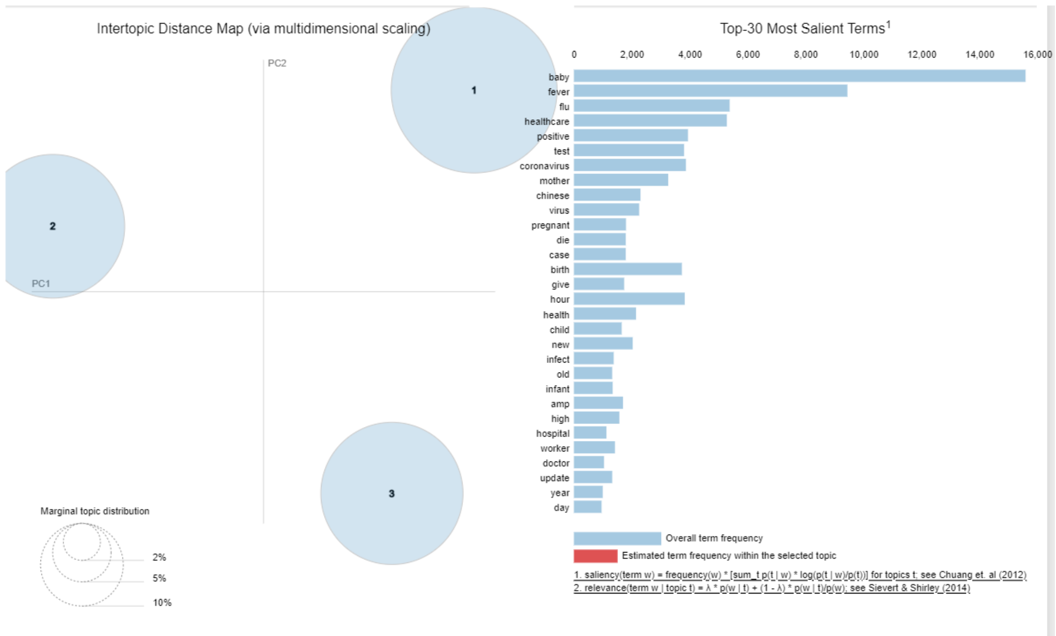

Figure 9: Inter-topic distance map

Furthermore, the 3 topics were again visualized using t-SNE which is shown in Figure 10. Here each of the dots represents a tweet and the three colors separates the topics.

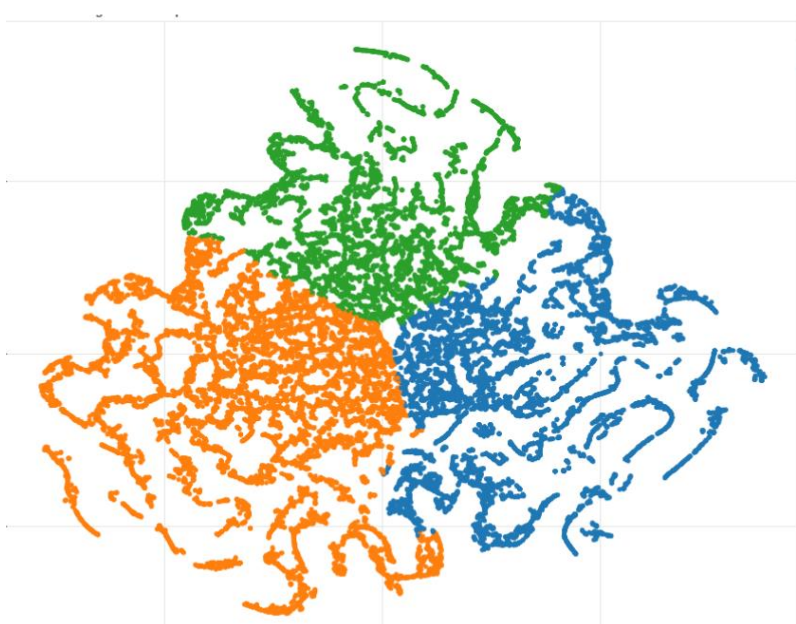

Figure 10: Clustering of tweets

After classifying the tweets, the sentiment behind each of the tweets was measured with respect to polarity and subjectivity shown in Figure 11. The value of polarity ranges from -1 to 1. The value of -1 represents highly negative experience, 1 represents good experience and 0 represents neutral experience. For subjectivity, the value ranges from 0 to 1. If a tweet contains a greater amount of personal opinion, then the subjectivity value would be close to 1 and if it contains factual information then the value would be close to 0.

Tweet number	Dominant_Topic	Topic_Perc_Contrib	Keywords	tweet	actual_tweet	act_tweet	polarity_vader	subjective
31428	2	0.7657	flu, positive, test, coronavirus, birth, chinese, virus, hour, new, pregnant	[horrible, baby, test, positive, coronavirus, hour, birth]	THIS IS HORRIBLE.\r\nBaby tests positive for coronavirus just 30 hours after birth https://t.co/...	horrible baby test positive coronavirus hour birth	-0.8816	0.772727
31429	2	0.6648	flu, positive, test, coronavirus, birth, chinese, virus, hour, new, pregnant	[chinese, baby, positive, hour, birth]	Chinese baby positive for coronavirus 30 hours after birth https://t.co/IBYvJ7xe19	chinese baby positive hour birth	-0.7184	0.272727
31430	2	0.7250	flu, positive, test, coronavirus, birth, chinese, virus, hour, new, pregnant	[baby, test, positive, coronavirus, hour, birth]	Baby tests positive for coronavirus just 30 hours after birth https://t.co/R3XLStSZbJ	baby test positive coronavirus hour birth	-0.7184	0.545455
31431	0	0.6667	baby, fever, mother, give, child, hour, old, birth, year, day	[pregnant, baby, baby, fever]	So everyone around me pregnant or has a baby. Baby fever on 10000000000000000 <U+0001F629><U+00...	pregnant baby baby fever	0.0000	0.500000
31432	2	0.7250	flu, positive, test, coronavirus, birth, chinese, virus, hour, new, pregnant	[baby, test, positive, coronavirus, hour, birth]	Baby tests positive for coronavirus just 30 hours after birth https://t.co/ska3Fuf7rc	baby test positive coronavirus hour birth	-0.7184	0.545455
31433	0	0.4446	baby, fever, mother, give, child, hour, old, birth, year, day	[baby, flu]	My baby really got the flu <U+0001F622>	baby flu	-0.4336	0.000000
31434	1	0.5555	healthcare, health, amp, high, help, worker, update, people, medical, public	[spread, recent, case, protect, workplace]	With the spread of #Coronavirus across #China, and recent cases appearing in the US, what action...	spread recent case protect workplace	0.3818	0.250000
31435	0	0.8335	baby, fever, mother, give, child, hour, old, birth, year, day	[real, sick, yesterday, feel, bite, well, able, eat, today, body, laugh, yesterday, dear, flu, d...	Been REAL sick, but yesterday I was feeling a bit better. Able to eat and all that. Well today, ...	real sick yesterday feel bite well able eat today body laugh yesterday dear flu die hole	0.0880	0.575000
31436	1	0.5138	healthcare, health, amp, high, help, worker, update, people, medical, public	[accord, doctor, specialize, public, health]	Here's what #Travelers need to know about the #coronavirus according to a doctor specializing in...	accord doctor specialize public health	0.0000	0.066667
31437	2	0.7647	flu, positive, test, coronavirus, birth, chinese, virus, hour, new, pregnant	[chinese, baby, test, positive, new, hour, birth]	OMG!\r\nChinese baby tests positive for new coronavirus just 30 hours after birth https://t.co/E...	chinese baby test positive new hour birth	-0.7424	0.333333

Figure 11: Sentiment analysis

In below Table 1 the mean polarity and subjectivity values are calculated. The mean polarity of topic 1 and 3 conveys negative emotion and the other topic have fairly positive emotion. However, as the negative and positive polarity tweet negate each other, each topic needed to be studied separately according to sentiments.

Table 1: Average polarity and subjectivity depending on topics

Dominant topic	Average polarity	Average subjectivity
1	-0.003856237	0.3548346
2	0.065616866	0.3669842
3	-0.199848470	0.3639693

First, sorting the dataset for only Topic 1 with negative polarity which essentially means negative sentiment and running a n-gram analysis presents the following shown in Table 2. The n-gram analysis shows that mothers are worried about their babies catching fever and also how pregnant mothers are severely affected by COVID-19.

Table 2: N-gram analysis of negative sentiment tweets of Topic 1

frequency	n-gram
9	baby fever time high
9	baby fever hit hard
8	mother lose battle covid
7	watch response coronavirus watch baby wrong
7	watch response coronavirus watch baby
7	watch response coronavirus watch
7	response coronavirus watch baby wrong
7	response coronavirus watch baby
7	new mother lose battle covid day
7	new mother lose battle covid
7	new mother lose battle
7	mother lose battle covid day birth
7	mother lose battle covid day
7	lose battle covid day birth

On the other hand, on the same topic tweets that express positive sentiment mostly talks about how pregnant mothers are surviving the coronavirus. The n-gram analysis of that portion showed in Table 3

Table 3: N-gram analysis of positive sentiment tweets of Topic 1

frequency	n-gram
6	mother covid birth child
5	couple separate window lockdown
3	visit wife nurse home
3	thing news people help
3	survive covid pregnancy daughter birthday
3	survive covid pregnancy daughter
3	scary thing news people help
3	scary thing news people
3	precious child ask hygiene item
3	precious child ask hygiene
3	nurse help deliver plane
3	mom survive covid pregnancy daughter
3	mom survive covid pregnancy

Now in the case of Topic 2 tweets that convey negative emotion mainly talk about how healthcare providers are having a very difficult time because of the risks and huge number of patients shown in Table 4.

Table 4: N-gram analysis of negative sentiment tweets of Topic 2

frequency	n-gram
30	provider care sick patient
30	healthcare provider care sick patient
30	healthcare provider care sick
27	provider care sick patient community
27	care sick patient community
26	sick patient community risk
26	care sick patient community risk
19	require healthcare provider covid patient
19	require healthcare provider covid
19	provider covid patient cost profit
19	provider covid patient cost
19	president require healthcare provider covid
19	president require healthcare provider

However, the positive sentiment tweets talk about helping healthcare agencies to tackle the spread of the virus shown in Table 5

Table 5: N-gram analysis of positive sentiment tweets of Topic 2

frequency	n-gram
33	look_donate healthcare patient pandemic
21	work healthcare provider month
21	time help work healthcare provider
21	time help work healthcare
21	help work healthcare provider month
21	help work healthcare provider
21	difficult time help work healthcare
21	difficult time help work
16	public coronavirus pandemic healthcare access
16	public coronavirus pandemic healthcare
16	pandemic healthcare access care read
16	pandemic healthcare access care
16	healthcare access care read

If focused on the n-gram analysis of the negative emotions' tweets of Topic 3, authors found the mothers are worried about their babies testing positive for coronavirus. Table 6 below demonstrates that.

Table 6: N-gram analysis of negative sentiment tweets of Topic 3

frequency	n-gram
103	covid patient nurse home
98	baby test positive coronavirus
73	newborn baby test positive
56	covid positive patient nurse
54	positive patient nurse home
51	test positive coronavirus hour
51	newborn baby test positive coronavirus
51	covid positive patient nurse home
47	test positive coronavirus hour birth
47	positive coronavirus hour birth
44	baby test positive coronavirus hour

On the contrary, the positive tweets of Topic 3 usually talk about how mothers are getting care by healthcare workers and the prevention strategy of widespread testing taken by the healthcare facilities.

Table 7: N-gram analysis of positive sentiment tweets of Topic 2

frequency	n-gram
6	spread nurse home resident facility
6	mother care facility nurse home patient
6	mother care facility nurse home
6	care facility nurse home patient
6	begin_she spread nurse home resident facility
6	begin_she spread nurse home resident
5	test coronavirus begin_she spread nurse home
5	test coronavirus begin_she spread nurse
5	perfect_storm death risk nurse home
5	increase test coronavirus begin_she spread nurse
5	increase test coronavirus begin_she spread

Upon carefully examining the tweets with a specified list of keywords regarding healthcare inequality authors found out that majority of the tweets that talk about racial inequality in healthcare are in Topic 3. A word cloud is depicted in Figure 12 to show the racial inequality related tweets.

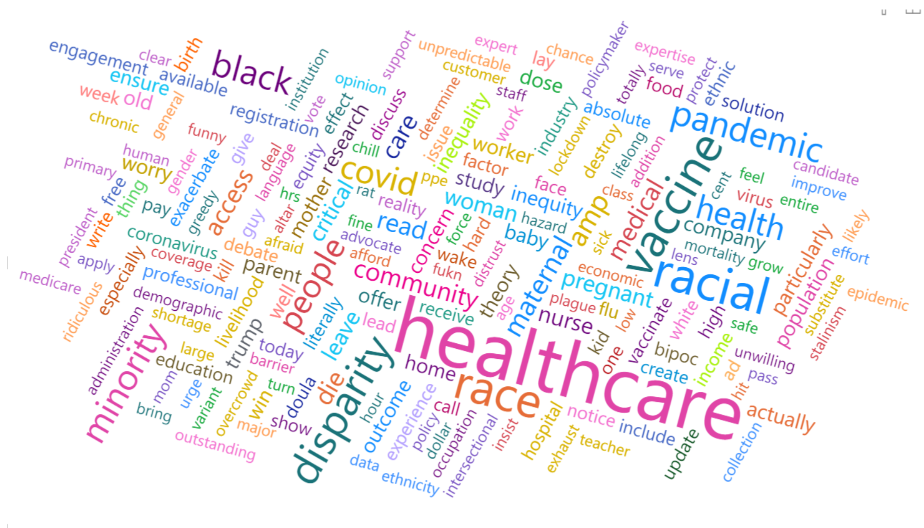

Figure 12: Word cloud of the tweets about racial inequality in healthcare

An n-gram analysis of the following tweets found that African American mothers are worried about not getting proper healthcare service. The n-gram analysis is shown in Table 10

Table 8: N-gram analysis of racial inequality tweets

frequency	n-gram
3	black people
2	write healthcare legislation
2	write healthcare
2	woman die childbirth vaccine well thing
2	woman die childbirth vaccine well
2	woman die childbirth vaccine
2	woman die childbirth
2	woman die
2	well thing focus
2	well thing
2	way prefer insurance company pandemic write
2	way prefer insurance company pandemic
2	way prefer insurance company
2	way prefer insurance
2	way prefer
2	vaccine well thing focus

Some of the actual tweets posted by the users are depicted in Figure 13

Figure 13: Tweets regarding maternal healthcare inequality

These representative tweets say a lot about the racial injustice in healthcare in USA which was especially aggravated during the COVID-19 pandemic.

Chapter 5: Discussion

In this study, authors have analyzed the tweets to extract maternal patient experience and classified the different topics patients are talking about and the sentiment behind each of them. As we can see topics have distinct levels of sentiment associated with them which shows the diversity of patient experience. Another aspect to note is that, on social media not only patients but also their relatives post their experiences which give various perspectives on medical care. The observed result from the LDA model classifies tweets into different topics which help to narrow down the patient's experience. Additionally, the sentiment analysis part provides meaningful information regarding the maternal patient experience. Moreover, through the N-gram analysis authors provided exactly what is discussed in each topic and critical insights regarding racial inequity in healthcare systems. However, there are a few limitations associated with analyzing Twitter data. For instance, users often use non-standard text, incorrect English, multi-lingual content and emojis to express their opinion, which makes it incredibly challenging for NLP to accurately classify some of the tweets and calculate the sentiment. Also, users tend to use sarcasm to express their opinion, which is very complex for the program to understand. There are also spelling mistakes or incomplete sentences which makes it difficult for the model to understand the underlying sentiment. To ensure that these algorithms provide valuable information, it is essential to preprocess the data. However, computers may not be able to distinguish between similar words such as "doctor" and "physician" or identify that "meal" and "meals" convey the same information. Additionally, spelling errors may also create further complications since a minor modification in a word can result in the computer perceiving it as entirely different. These constraints are solved by using stemming or lemmatizing to reduce words to their base form, utilizing NLP libraries to correct spelling errors, and manually analyzing comments to identify context-specific words and replacing them with common words. Preprocessing patient-derived data may be more complex since respondents may have limited healthcare literacy, make spelling mistakes, or use texting language that is not part of the NLP library used for processing. Besides, sometimes tweets contain phrases that do not convey the literal meaning of the words which makes it difficult for the program to understand. For instance, by using the phrase ‘baby fever’ users usually express the longing that some people experience relating to the desire of having a child of their own. However, the computer program interprets the literal meaning of the phrase, for this reason, the program fails to extract the proper sentiment from tweets. Nevertheless, above all these limitations the model produces an initial insight that gives policymakers an indication to capture patient experience to improve healthcare systems and understand system-level concerns for the under-represented communities.

Chapter 6: Conclusions

The analysis of this study would work as a guideline for the policymakers inside a healthcare system. Since, among the developed countries in the world, the US has the highest rate of maternal mortality or morbidity, analyzing patient experience can provide valuable insights regarding patients' expectations of care and the original care quality that they received. Utilizing the topics identified using topic modeling, policymakers can understand the patient's negative and positive experiences and layout policies according to that. Moreover, social media analytics provides an initial insight into the healthcare disparities from the system-level point of view that are not captured in patient experience surveys or other tools. One recommendation for future work would be to include other social media data and data from different languages. Since there are a lot of multilingual users in social media, the model would be able to capture more information. Additionally, a different approach such as Machine learning can also be used to classify the topics. Another important addition can be using Process mining techniques to find out the patient journey map and take necessary action to improve the quality of care. If policymakers have access to the surveys of the patients' experience collected through interviews, this data can be incorporated into the model to get much more insights to improve healthcare quality.

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Vita

Debapriya Banik started his MS in Industrial Engineering program in University of Texas at El Paso in Fall 2021. His main focus of research was in the field of Healthcare data analytics under the careful supervision of Dr. Sreenath Madathil and Dr. Amit Lopes. In 2022 he presented a paper in IISE Annual conference 2022 titled “Data-Driven Decision Making for Predicting Products' Unmet Demand in A Blood Products Supply Chain” which was later published.

Debapriya got his BS in Industrial and Production Engineering from Rajshahi University of Engineering and Technology, Bangladesh. From his very early years in college he was always motivated to solve problems using different data analytics tools. Which made him pursue higher degree in this field.

In 2022, he interned in Helen of Troy as Supply Chain Management (intern) where he proved his analytics skill to make process more efficient. Debapriya will be joining Cummins Inc. as a Supply Planning Analyst from June 2023.