Analyzing Public View towards Vaccination using Twitter

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ANALYZING PUBLIC VIEW TOWARDS VACCINATION USING TWITTER

A thesis submitted in partial fulfilment of the requirements for the degree of Master of Science in Computer Engineering

By

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I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Rutuja Mahajan ENTITLED Analyzing Public View towards Vaccination using Twitter BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science in Computer Engineering.

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Abstract


Educating people about vaccination tends to target vaccine acceptance and reduction of hesitancy. Social media provides a promising platform for studying public perception regarding vaccination. In this study, we harvested tweets over a year related to vaccines from February 2018 to January 2019. We present a two-stage classifier to: (1) classify the tweets as relevant or non-relevant and (2) categorize them in terms of pro-vaccination, anti-vaccination, or neutral outlook. We found that the classifier was able to distinguish clearly between anti-vaccination and pro-vaccination tweets, but also misclassified many of these as neutral. Using Latent Dirichlet Allocation, we found that two topics were sufficient to describe the corpus of tweets. These dealt with: (1) consequences of vaccination/non-vaccination, and (2) promotion of vaccination/non-vaccination. Finally, using the NRC emotion lexicon, we found practically significant differences in emotions expressed about vaccination between vaccine outlooks, but no practically significant temporal differences across a year.
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1 Introduction

1.1 Overview

According to the World Health Organization, a vaccine is a biological preparation that improves immunity to a particular disease. Vaccinology was founded by Edward Jenner in 1796 after he inoculated a 13 year-old-boy with vaccinia virus (cowpox) demonstrating immunity to smallpox. Edward Jenner’s innovation provided the breakthrough for health science and thus in 1798, the first smallpox vaccine was developed. Advancing in technology, methods for growing viruses in the laboratory led to rapid discoveries and innovations, now resulting in eradication of many infectious diseases and amplifying influenza tolerance. Nowadays, vaccines are widely recognized by health authorities and the medical community as a major tool for accomplishing public health success.

Different types of vaccines have been designed to teach how to fight off certain kinds of germs. Vaccines are being developed based on how your immune system responds to a germ, who needs to be vaccinated against the germ, and the best technology or approach to creating the vaccine. Based on these factors, vaccines are mainly divided into 4 categories [57]:

1. Live-attenuated vaccines: Using a weakened form of germ similar to the natural infection so that they can prevent a strong, long-lasting immune response.

2. Inactivated vaccines: Using a killed version of germ that causes a disease. The effects are temporary.

3. Subunit, recombinant, polysaccharide, and conjugate vaccines: Uses specific
4. Toxoid vaccines: Uses toxin made by germs to create immunity to the parts of the germ that cause disease instead of the germ itself.

Innovative techniques now drive vaccine research, with recombinant DNA technology and new delivery techniques leading scientists in new directions. Disease targets have expanded, and some vaccine research is beginning to focus on non-infectious conditions such as addiction and allergies. Despite being recognized as one of the most successful public health measures, for many individuals, these achievements are not adequate to embrace vaccination wholeheartedly. They doubt the benefits of vaccines, worry over their safety and question the need for them, an attitude referred to as vaccine hesitancy [37].

In the last decade, advancements in research have yielded lots of benefits for vaccines. However, the same time span has also seen a substantial increase in the rate of people expressing their concern over the safety of vaccines. Some of the influencing elements supporting this controversy are ingredients included in the vaccine, presence of thimerosal, adverse effects of vaccination such as claims from the anti-vaccination group about vaccination leading to autism and associating influenza vaccine with Guillain-Barré syndrome. These reports have resulted in the emergence of negative attitudes such as vaccine hesitancy, vaccine refusal, vaccine skepticism. An attitude of hesitancy differs from an action of vaccine refusal. Even those who are vaccinated can harbor hesitancy towards certain aspects of vaccination.

The onset of these controversies dates back to 1995 when a former British doctor Andrew Wakefield and a group of researchers hypothesized a possible link between Measles, Mumps, and Rubella (MMR) vaccine and autism. This hypothesis had been suggested previously by a few researchers as well, such as Fudenberg in a small pilot study published in a non-mainstream journal and
Gupta in a review of possible treatments for autism [101,102]. However, the hypothesis had not been systematically explored until then.

In 1998, Wakefield along with 12 co-authors published an article based on the case series study in the prestigious medical journal ‘The Lancet’ supporting the hypothesis to be correct [95]. The news was publicized by press outlets resulting in frightening parents who delayed or completely refused to vaccinate their children. The public reaction to the article resulted in the plummeting of vaccination rates in the United States of America and the United Kingdom.

Public concerns around vaccination encouraged researchers to investigate deeper into the studies. Over the next twelve years, no relevant or reputable study confirmed Wakefield’s findings. Instead many well-designed studies claimed to have found no link between MMR and autism. Eventually, in 2010 Lancet retracted the paper and Wakefield was banned from practicing medicine in Britain for his deception and ‘callous disregard’ for children in his care for the course of research. Until then, families in the United Kingdom noted more than 12,000 claims for measles and hundreds of hospitalizations with serious complications.

Stunningly, the rumor of possible link between vaccine and autism still persists and was amplified by media and endorsements from celebrities. Wakefield started campaigning on his own and created a documentary film ‘Vaxxed’ alleging a cover-up by the Center for Disease Control and Prevention (CDC) of the proclaimed link between vaccine and autism. Consequences of Wakefield’s relentless pursuit towards attesting his theory contributed to a four-fold increase in measles cases in Europe and many deaths in 2017. A measles outbreak in Disneyland in California in 2015, infecting more than 147 people and another outbreak in Minnesota in 2017 with over 79 cases of measles are the outcome of Wakefield’s anti-vaccine fanaticism where his message persuaded many parents to not vaccinate their children [96,97].
The vaccine-autism myth critics targeted other vaccines for scrutiny and turned their questions to thimerosal, a preservative containing mercury used in some vaccines. In 1999, the U.S Food Drug Administrative (FDA) and the Institute of Medicine performed a comprehensive study and found no association between mercury in vaccines and neurodevelopment disorders. Even after thimerosal was removed from almost all childhood vaccines, autism rates continued to increase [98]. Refusal to vaccinate has also led to the influenza killing 100 to 300 children under the age of 5 each year, and up to 85% of them were not vaccinated.

1.2 Public Perception towards Vaccine

Given the rapid changes in the communication landscape brought about by participative internet use and social media, sharing news or knowledge can be achieved effortlessly. In recent times, Twitter has been placed as one of the popular mediums for social networking and microblogging. Twitter users also known as twitterers post and interact with messages which are known as tweets. With the arrival of Twitter, twitterers can share their views by posting a tweet, promote a campaign by retweeting or express their opinion by using hashtags for various topics of their interest. With these conveniences follow its impact on mundane life.

Generally, the development of any information related to the vaccine or a certain event provokes interested twitterers to either react or promote their perception towards the affair. Some of these twitterers express their satisfaction towards the role of vaccination for the betterment of mankind while some perceive vaccines as a risk to humans. Some of the twitterers remain skeptical because of insubstantial evidence while some of them outwardly refuse to even consider vaccine benefits because of their traditional beliefs. Given this wide range of views towards vaccination, Twitter has proven to be a beneficial
Figure 1.1: CDC promoting HPV vaccine
<table>
<thead>
<tr>
<th>Types of People</th>
<th>Tweets</th>
</tr>
</thead>
</table>
| Vaccine Promoters or Acceptors | As flu season continues, please remember to get vaccinated, stay home if you’re feeling sick, and wash your hands often.  
RT @Jacques_dH: Vaccination has proven benefits, it is a must to protect the population from preventable deadly diseases. @CPME_EUROPA  
Man, if only there was a vaccine! |
| Vaccine Rejectors | @Thomas1774Paine Its about WEALTH, not HEALTH for most MDs in practice today. #VaccinesKill  
@newsycombinator: Why does drug resistance easily evolve but vaccine resistance does not?  
If you do anything other than encourage the vaccination of the child, you fail as a friend. |
| Vaccine skeptics | This is quite a thing. - - A Vaccine Against ... Cancer?  
RT @DailyMirror: I don’t know if I should stop my teenage daughter having the HPV vaccine  
What are they putting in our vaccines? |
| Passive Acceptors | @colleengrott That is scary. I’ve never had that vaccine, only the flu vaccine as it was required for work purposes  
@mainecoon03 @FoxNews @CDCgov Sad thing is how many hospital systems mandate that employees obtain the flu vaccine.  
My mom works in two different hospitals as an ICU nurse and she was forced to take an ineffective vaccine. |

Table 1.1: Types of people based on their perception towards vaccine resource to understand the perception of people towards vaccination.
2 Literature Review

This chapter illustrates the successful execution of employing social media as a data mining tool on varied platforms.

2.1 Social media for commercial applications

Social media outreach has increased substantially over a decade, increasing connectivity amongst people. Furthermore, the lack of constraints put on social media encourages their users to candidly express their thoughts. Being avidly used, social media has garnered attention from researchers to analyze the public behaviour and structure [15]. Analysts have explored the benefits of practicing social media to forecast real-world outcomes such as stock market rates, box-office revenues and to analyze social ties and to mine opinions [11,12,13,14]. Studies performed on social media applications such as for weblogs, Facebook, chat boxes and Twitter have proven to be useful to generate results to mine data and corresponding analyses [16,17,18,19].

A study done by Pagolu et al. on the stock market investigates how changes in the stock market correlate with public opinions [1]. The authors collected 250,000 tweets from August 2015 to August 2016 based on keywords related to Microsoft. The authors used 3216 tweets to annotate manually based on positive, negative and neutral sentiment for training the machine learning model. The features were extracted based on n-grams and word2vec representation. To analyze the correlation between price and sentiment the authors developed a program that labeled the current day stock price as 1 if there was an increase in the stock price otherwise was labeled as 0. The authors calculated total
positive, negative and neutral emotions successively in tweets in a 3-day period and used them as features for a classifier model to label the next day value as 0 or 1. The model was trained on 90% of the labeled tweets.

Both feature sets, when applied with random forest, provided 70.2% accuracy for the word2vec model and 70.5% for n-grams model. The authors chose to utilize the word2vec model even though it provided slightly less significant results than n-grams due to its scalability and sustainability powers. The finalized model showed the accuracy of 69.01% when trained using logistic regression using 80% of the data as the training set and 71.82% accuracy was noted when the 90% of data was modeled using libSVM thus depicting the good correlation between public sentiment towards the stock market in Twitter and stock market changes.

Given the broad-spectrum Twitter analysis can be done, another study performed by Kim et al. attempted to classified tweets about e-cigarettes into distinct categories [2]. The authors extracted tweets from Twitter from November 2014 to October 2016 based on 158 related keywords collecting over 11.5 million tweets from 2.6 million unique users. The users were categorized into five groups: individuals, informed agencies, marketers, spammers and vapor enthusiasts. Six coders were assigned to label the tweets by reviewing the user’s profile page along with their profile description and recent tweets on their timeline which can or cannot be related to e-cigarettes.

The classifier model was created to predict against two feature sets. The first feature set consisted of metadata features such as geolocation enabled, followers count, retweet count and number of tweets favorited by user, while the second feature set of derived features comprised of behavior and linguistic content of the user profile along with statistical summary of user’s tweets such as number of keywords that occurred in a tweet and hashtags count. Features missing more than 10% of data were dropped while mean imputation was
performed on the features missing 10% or fewer data. Additionally, machine learning algorithms were applied to identify the best classifier model.

The authors designed the model on manually labeled on 200 manually labeled tweets and 4897 labeled users. The authors claimed that Gradient Boosting Regression Trees served as the best model amongst other machine learning models by providing the highest F1 score of 83.3% using both metadata and derived features while it dropped to 72.7% using only metadata features. The authors performed a t-distributed Stochastic Neighbor Embedding to visualize the discrete clusters formed by five categories of users. Furthermore, to analyze the contribution of each feature towards the prediction model, features were evaluated based on Gini Importance exhibiting that Status count and Followers count contributed as most pertinent features amongst others.

An array of diverse studies on commercial platforms attests to social media as a strong platform to analyze temporal data for public emotions. A study predicting stock market indicators such as VIX and Dow Jones through Twitter discovers a high correlation amongst emotions like hope and fear and stock market indicators [3]. Furthermore, studies claim to have a cause and effect relationship amongst public sentiments or emotions towards closing stock prices and trading volume [4] [5].

Additional studies by Kang et al. analyze the network of vaccine sentiment on social media to understand context-specific causes underlying vaccine hesitancy better [6]. The tweets were gathered using a web-scraping tool ChatterGrabber along with their webpage links. The authors harvested 26,389 tweets with 8416 unique weblinks between April 16, 2015, to May 29, 2015. The authors screened the top 100 of the most shared links and randomly sampled 50 for further analysis. Three raters coded the tweets as positive, negative and neutral manually on a sample set of 10 tweets. A word network for each sentiment was analyzed to evaluate the concepts underlying each sentiment.
The most central concepts around positive sentiment were found to be parents, measles and autism, while most central concepts around negative sentiments were found out to be children, thimerosal and CDC. The most significant concepts related to neutral sentiment were SB 277, antivaccination, parents and children. The sentiment network for positive and negative sentiment exhibited structural similarities in terms of the size of the network and average path length.

2.2 Social media for Healthcare

Social media has paved the way to provide robust results in the realm of healthcare. A study by Greaves et al. acknowledges social media to distinguish poor health care quality based on a patient’s experience [21]. The study mined information related to the corresponding study from rating and feedback websites, discussion forums, blogs, and social networks. Standard Natural Language Processing tools were employed to analyze sentiments and identify themes within the data. The resulting key themes were cleanliness or emotions such as anger, joy or sadness. This information, taken together with traditional surveys and can be used by health system regulators to perceive their service as poor performance when a pre-defined warning threshold was crossed. It also helped clinicians and managers to address the scope for improvement.

Another study by Househ [22] refers to using social media as a platform for healthcare professionals to interact with patients by providing relevant information, support, tracking personal progress and goal settings. Recognizing the widespread use of social media in healthcare, the study reviewed its impact on healthcare organizations, clinicians and patients.

As stated by the study [22], 70% of the U.S. healthcare organizations use social media for fundraising, news and information spread and advertising new services, thus attracting new patients to use social media for the purpose.
However, a comprehensive analysis of a patient’s state is not achieved by the organization unless a high level of interaction with the patient is procured. Physicians usually read news articles and research new medical developments, communicate with colleagues regarding patient issues. However, they rarely communicate with patients directly to stick with ‘appropriate boundaries of patient-physician relationship’. Although a large percentage of physicians favored interactions with patients on social media to support patient education, monitoring their health would lead to better outcomes. One of the challenges is maintaining the integrity of the ethical code such as maintaining privacy and confidentiality [23].

Patients benefit the most from using social media by expressing their experiences, reading discussion forums, information and news articles. Their reviews bolster and uplift other patients’ goals and support such as weight loss, tobacco cessation, and physical activities, thus making a case for the positive impact of social media for health organizations at each level [24].

Even though social media is considered to be a promising tool for health promotion, it requires careful attention and may not always achieve the desired outcome [25]. To investigate this, Korda et al. studied current events to understand the impact of social media on healthcare promotions and behavior change. The study scans the reviews events from meta-analysis, white-papers and reports from foundations and federal and public health agencies, private, public and non-profit organizations corresponding to healthcare.

The study concluded that social media intervention improves healthcare and has positive effects of empowerment, although the results of this are scantily perceivable. Evaluating the effectiveness of behavioral change by incorporating web-based or face-to-face interventions delivered positive effects on self-efficacy and mastery scales. Using tailored messages, key themes, applying various complementary modes to advertise, motivational emails or text messages exhibit
positive impact on healthcare.

### 2.3 Social Media for Communicable diseases and prevention

In a study by Broniatowski et al. sought to distinguish amongst influenza infection-related tweets with other healthcare-related tweets [6]. The authors downloaded the tweets through a health-related stream which consisted of 269 health-related keywords for eight months. These tweets were passed through three filters – health filter analyzing if the tweet is relevant to health, influenza filter analyzing if the tweet is relevant to influenza and infection filter analyzing if the tweet is indicative of an actual infection. The health filter utilized a combination of a keyword filter and support vector machine model for training. The influenza filter and infection filter utilized the logistic regression model to classify the tweets.

The features for creating these models were acquired from n-grams (two to three), and other linguistic information regarding message writing styles. The authors attempted to identify the geolocation of the tweets by using either the public information available on Twitter or geolocation system ‘Carmen’ and used the United States and New York city to estimate influenza prevalence in these locations. The tweets pertaining to the geolocations were extracted for further analysis.

The model was tested against influenza-like illness surveillance network data released by the CDC after 2 weeks along with a basic keyword filtering model. The results of the infection model trained by the authors closely matched with CDC data while the basic keyword filtering model showed largely varying results thus confirming the model built as the best model. Though the study provided promising results, it lacked comparison with different training models built for the analysis.
Another study by Lazard et al. attempted to detect themes of public con-
cerns during the 2014 Ebola outbreak [27]. The study mined tweets during
a live Twitter chat using ‘CDCchat’ hashtag on October 2, 2014, successively
removing tweets related to CDC and other health institutions resulting in 2155
tweets overall. The tweets were analyzed using SAS Text Miner software to
parse and extract information from tweets and gather insights from unstruc-
tured data. The authors finalized eight themes within the text information
which composed of modes of contracting Ebola, possibility of Ebola transferring
through air, ways to protect oneself, how and where Ebola survives outside the
body, fear of traveling in general or specifically to Africa, symptoms of Ebola,
discussion of the event itself and subconversations which occurred during the
chat.

The number of tweets in each theme estimated its significance. The highest
number of tweets were observed under the topic of symptoms of Ebola and its
transmission. Fear of travel was the second most significant theme while tweets
addressing the transmission of Ebola through the air were scantily produced.

A similar study was performed by Miller et al. exploring tweets related to
Zika and its underlying four characteristics as symptoms, transmission, preven-
tion and treatment [28]. The authors designed a two-stage classifier model, one
to distinguish relevant tweets and others to distinguish the tweets in four cat-
egories. Topic modeling using Latent Dirichlet Allocation (LDA) was applied
to each category to determine five main topics for each disease characteristic.

The authors extracted in all 1.2 million tweets from February 2016 to
April 2016 using Twitris 2.0 using relevant keywords. Three microbiology
and immunology experts annotated 1467 tweets as relevant or not regarding
Zika. Annotated relevant tweets were further coded for each disease category
as Symptoms if the tweet related to symptoms associated with Zika, Transmis-
sion if the tweet mentioned modes of transmission for Zika virus, Prevention
if the tweet noted ways to prevent Zika and Treatment if the tweet contained any information about treatment. Supervised classification algorithms such as decision trees, naïve Bayes, bagging and bootstrapping were demonstrated for a two-stage classifier. Fleiss kappa was calculated to measure interreliability agreement amongst raters. Features were generated from unigrams resulting in multinomial naïve Bayes outperforming all models providing area under the curve of 0.94 for both classifier models. The number of topics for topical analysis was determined by the perplexity score.

Another study by Lampos et al. reported administrating a monitoring tool to measure the prevalence of the H1N1 flu pandemic [29]. The authors held the study in the United Kingdom for 24 weeks from June 4, gathering 160,000 tweets. The study focused on the 54 most populated urban centers and restricted the geolocation parameter to a 10 km radius. The results were tested against the Health Protection Agency’s (HPA) weekly reports.

The authors pre-compiled a list of Influenza-like Illness (ILI) markers from n-grams of 41 keywords and computed the flu score as a number of markers it contained divided by the total number of markers used. Flu score for the daily Twitter corpus was calculated as the sum of all flu scores divided by the total number of tweets. The geolocations were subsequently grouped into five regions. To match the flu scores with HPA’s flu rates, weight is assigned to each marker before computation and the performance of the model as indicated by the linear correlation coefficient between the inferred model and HPA’s official flu rates. The average linear correlation between all five regions is estimated to be 94.12% with a standard deviation of 1.54%.

To generate the ILI markers automatically, unigrams are extracted from encyclopedic and informal references where potential flu patients share their experience, resulting in 1560 stemmed candidate markers followed by computing their daily, region and unweighted flu sub-scores. Least Absolute Shrinkage and
Selection Operator (LASSO) regression was implemented to rank candidate features and penalize redundant terms generating 97 stemmed markers.

2.4 Social Media to Analyze Vaccine

Having a platform for expressing your views without any restrictions has piqued the interest of researchers trying to decipher human behavior for several topics across the world. One such study done by Salathe et al. on H1N1 pandemic virus vaccination provides promising results from extracting tweets through Twitter to analyze vaccination sentiments [7]. In this study, the authors harvested 477,768 tweets related to vaccine using 9 different keywords. These tweets were then categorized into four categories: positive, negative, neutral and irrelevant. Each tweet in the training set was labeled by 44 undergraduate students with the benefit of getting a credit hour. The study also extracts user information to track the information flow among users and created a network of users based on their sentiments.

For classifying tweets based on the sentiments, the authors used an ensemble method combining naive Bayes (to determine positive and negative tweets) and maximum entropy classifiers (to determine neutral and irrelevant tweets). Feature selection methods such as applying stopwords, removing punctuation marks and stemming the tweets were also implemented to increase the performance of the classifiers. The location of users was also extracted to incorporate with the user network. The authors claims that communities are either dominated by positive or negative sentiments towards the novel approach of the H1N1 vaccine. Also, the information is more likely to flow between communities who share the same sentiments towards the vaccine rather than those who do not (opposing ones).

Even though the author claims to have provided robust results, it doesn’t attest to the validity of students rating the tweets. Furthermore, no quan-
tifiable results were provided. Furthermore, the authors did not evaluate how Placefinder helped with geolocations.

Additional studies by Zhou at al. attempt to classify anti-vaccine opinions [9]. Tweets were collected from October 2013 to March 2014 where two raters labeled a sample of 2098 tweets as anti-vaccine opinioned tweets. User information for each tweet generator such as the users the generator followed (sources) or the users following the generator (followers) was taken into account while training the classifier model. The tweets were sampled into two sets of the continuous three-month period for training and testing. The features utilized to train the models composed of unigrams, bigrams and social connection features such as followers and sources. Pertinent features from these were retained based on their significance using a hybrid approach of forwarding and backward feature elimination. Resulting features were modeled to classify tweets as anti-vaccine using support vector machine as a machine learning algorithm.

By the virtue of Fisher’s exact test and Bonferroni’s corrections on features of textual data, it is revealed that text-based features lose their significance along with time as a contrast with social connection features. The classifier performed roughly the same for classifying models based on only text content features (89.4%) and using social connection features (89.8%) in terms of accuracy for SVM algorithm. The authors claim the connection feature model to be more reliable as the connection features amongst users tended to be stable within the defined time period. The best performing classifier was retrieved by using a combination of social connection and text-based features (94.4% accuracy). Furthermore, the study reports that information about sources might be more beneficial to predict the direction of the user’s expressed opinion rather than followers. Moreover, users sharing the same opinions or views are more likely to be better connected than others.

An extension of this study performed by Dunn et al. attempts to associate
public exposure to negative opinions about Human Papillomavirus (HPV) vaccines with the resulting negative expression amongst the social structure of Twitter users [9]. The authors utilized the same tweets as their previous study which were classified as negative if they reject the safety of the HPV vaccine or promoted it, otherwise as neutral. A sample of 2098 tweets was labeled by two raters. The timeline for each Twitter user posting at least on tweets related to HPV vaccines was created separately followed by the tweets posted by their followers. Prior exposure of the user to the tweet was indicated by compiling a list of tweets generated during the timespan. As exposure of a tweet increases per time, to avoid biased results, the prior exposure was set to be least at 3 exposures. Retweets were handled to measure information exposure amongst the user and the users’ followers.

To test their hypothesis developed in the previous study [9], the authors analyzed the number of times the user posted a negative tweet followed by the maximum of prior exposure and compared it against the number of times a posted tweet was negative when the maximum of prior exposures was neutral. The relative risk of posting a negative tweet related to prior exposure was calculated by these counts. Tweets were classified as negative by using the classifier modeled in the previous study classifying 25.13% of the tweets as negative in the defined timeline. The internal network for the information flow was studied by plotting the number of users tweeting about HPV vaccines against their total number of followers and the followers within the network of users tweeting about the HPV vaccine. The authors claimed that a higher proportion of users were exposed to more negative tweets than the percentage of user tweets being classified as negative. Furthermore, the study determined that the users exposed to more negative opinions were most likely to express negative opinions towards the HPV vaccine.
2.5 Vaccine Perception

Various studies have been carried out to understand public opinion, concerns, and perception towards vaccination. Parents play a pertinent role to channel views held by the public in society. A study by Olshen et al. analysed parental acceptance towards HPV vaccination by conducting a focus group and individual interviews [20]. The study recruited 25 parents from an urban, academic adolescent clinic and a suburban private pediatric practice into six focus groups and individual interviews. The parents were informed about the prevalence of HPV, complications of HPV infection and benefits of quadrivalent HPV vaccine along with open-ended questions before each session. Codes and themes were acquired with the help of transcripts. The authors delineated five themes from the codes as vaccines now available, unfamiliar with HPV, risks of acquiring HPV, the age for administrating HPV vaccine and administering HPV vaccines to boys and girls.

Vaccines now available comprised of parents being favorable to current vaccination strategies. Although parents were apprehensive towards side effects of vaccination, they believed that the benefits outweigh the risks given the rare occurrences of vaccine side effects. Physician recommendation weighed heavily on parental views. Parents unfamiliar with HPV were categorized in this theme. Parents having higher acceptance towards HPV vaccination believed their children would eventually get exposed to HPV and thus were aware of the risks of acquiring HPV. The huge disparity amongst parents regarding the age of children receiving the HPV vaccine was reported. Parents showed a positive reaction for immunizing both boys and girls.

A study by Dempsey et al. sought to unravel factors associated with parental acceptance of HPV vaccines [30]. Their objective is to determine overall acceptance for parents of preadolescent children, evaluate the influence
of written education provided to parents for HPV vaccine acceptance and to
discover individual predictors for parental acceptance of HPV vaccines. The
study was based on the response of a cross-sectional survey. The authors re-
cruited 1600 parents within the age range of 8-12 years by mailing them a
self-administered survey on knowledge, attitudes, and beliefs about HPV and
the HPV vaccine. To analyze the effects of enlightening parents with HPV
infection sequela, a randomized sample of half of the participants received a
detailed 2-page ‘HPV Information Sheet’.

The 67-item survey explored the attitudes about vaccines, knowledge, ex-
periences about HPV and Sexually Transmitted Infections (STI) along with
sociodemographic characteristics such as age, gender and religion [30]. The
outcome measure for overall parental acceptance based on 3 questions asked in
the survey for HPV vaccine was measured on an 11-point scale where 0 was
rated as ‘would definitely not allow’ to 10 as ‘would definitely allow’. Knowl-
edge access score was measured using a 7-item scale of True-False questions for
67 item surveys by calculating the number of correct responses within the over-
all responses while questions related to experience with HPV -associated illness
were measured on a 4-point scale. Questions regarding attitudes about vaccines
were based on 5 psychological constructs: the perceived susceptibility of dis-
ease, perceived severity of the disease, perceived benefits of the HPV vaccine,
perceived barriers to the vaccine and normative beliefs for the HPV vaccine.
Responses for these constructs were reported on a 5-point Likert scale. Ques-
tions from these five constructs served as predictors of parental acceptability of
HPV vaccines individually in a multivariate linear regression model.

The results were calculated amongst two groups: those who received only
a survey called a control group and those who received the ‘HPV Information
sheet’ along with the survey. The results of the study indicated that parents re-
ceiving the ‘HPV Information sheet’ scored higher on average on the knowledge
assessment than the control group. However, this did not affect the vaccine acceptability as there was no statistically significant difference between both groups. Multivariate regression analysis revealed that the perceived benefits of the HPV vaccine had a substantial effect on predicting vaccine acceptability. In conjunction with this, factors such as influence by peer groups, influence by physician recommendation, perceived susceptibility to HPV and STI's and personal experience were considered to predict the outcome of vaccine acceptability.

In another study Lenselink et al. interviewed 356 parents with children between the age group of 10-12 years with a closed-ended question designed as a survey regarding their acceptance of HPV vaccine for their children and their knowledge of HPV and cervical cancer [31]. The interview incorporated sociodemographic questions along with knowledge of risk factors for cervical cancer, the transmission of HPV, the relationship of HPV with cervical cancer, the development of HPV vaccine and its acceptance.

Overall 87.9% of parents interviewed exhibited acceptance of HPV vaccine after government approval while others wanted to perceive the effects of the HPV vaccine for several years as they were afraid of side effects. The same ratio of parents was willing to vaccinate both boys and girls. 19% of the parents indicated their approval for including the HPV vaccine in the National Vaccination Programme. The only important factor associating HPV vaccination acceptance was determined to be whether the parents have vaccinated their children with all recommended vaccines in general. Even though the survey was biased towards gender as most participants were female and had experience with a cervical screening program, they were unaware of the relation between HPV and cervical cancer.

Furthermore, a survey study by Ogilvie et al. concluded that the major factors corresponding to parents of girls enrolled in 6th grade concurring
to receive an HPV vaccine were its effectiveness, advice from physicians and concerns about their daughter’s health [32]. The prime factors associated with disapproving the vaccination were their concerns towards the safety of the HPV vaccine, preference to wait until their daughters reach an eligible age and lacking information to make an informed decision.

Shifting the focus of study from parental acceptance towards HPV vaccine to young adults Lenselink et al. conducted a cross-sectional survey for adults aged between 18-25 from two university departments and one non-university technical college enrolling 600 participants [33]. A self-administered survey composed of questions of demography, sexual activity, cervical carcinoma, Pap smears and acceptance of HPV 16 and 18 vaccines. Fisher’s exact test was implemented to test gender differences while univariate logistic regression was employed to examine the ability of variables distinguishing between participants accepting and rejecting the HPV vaccine. Determination of variables contributing individually towards the probability of accepting HPV vaccination was demonstrated by multivariate logistic regression with the forward selection method.

Two-thirds of the participants were female reflecting the gender distribution in the region. A small portion of participants were aware of HPV while the majority were aware of its relationship with cervical cancer. Despite more than half of the participants displaying willingness to receive HPV vaccination, men and older participants were less likely to agree. The study revealed that participants with lower age and females accompanied high vaccine acceptance rate whereas medical education, knowledge of HPV, cervical cancer and the cervical screening program had no significant effect on the vaccine acceptance.

Despite being the most effective preventive tools against many severe diseases, a large portion of people still refuse to accept vaccines resulting in outbreaks. Due consideration had been given to comprehend the rationale behind
this characteristic. One such study by Gust et al. focuses on factors influencing skepticism about vaccines and the reasons behind them [34]. Data were collected from 3924 responders of the National Immunization Survey (NIS) 2003-2004 followed by a telephone interview with the parent or guardian. A report on the child’s vaccination history was retrieved from records after getting consent from the parents. A survey module was attached to the NIS survey to procure national estimates of parents concerned about immunization and was requested to respond to a randomly sampled subset of parents who completed the NIS survey. The interviewers questioned parents about concerns regarding vaccines, a specific vaccine that prompts doubts, reasons to doubt and reason for those who delayed or refused a vaccine for their child.

The authors classified the parents into three categories: received vaccination for their children even being skeptical about it labeled as ‘unsure’, delayed vaccination for their child as ‘delayed’, and not vaccinating their child as ‘refused’. Predictors of the outcome comprised of demographic characteristics and depicted concern level on a 4-point scale from ‘very concerned’ to ‘not concerned at all’, for 2 vaccine-related issues of being vaccine not preventive for the disease and vaccine might not be safe or displays serious side effects. The significance of each predictor was investigated using logistic regression for each group.

More than a quarter of parents expressed doubts about immunization. 8.9% of parents reported accepting vaccination albeit falling under the unsure category, while 13.4% were reported for delayed and 6% parents refused to vaccinate their children. Unsure category was highly associated with factors as maternal age, maternal ethnicity, child’s age, geographic location, and concern about the vaccine not being safe. The delayed category was significantly associated with the child’s age, the number of children in the household, maternal marital status, and concern about vaccines not being safe. Factors such as
child’s age, maternal ethnicity, and concern about vaccines not being safe were significant predictors for refusal.

While determining which vaccines prompted skepticism amongst parents, it was revealed that among the unsure and refused group, the largest proportion of parents expressed their doubt for varicella vaccine and second largest proportion selected ‘not a specific shot’ as the vaccine causing doubts along with safety or side effects of the vaccine as their doubt promoter. The delayed group chose ‘not a specific shot’ in large proportion for prompting their doubts followed by varicella and MMR vaccine along with ‘child was ill’ as their main reason to delay the vaccine. A large proportion of parents listed ‘lack of information and assurance from healthcare providers’ as a mind changer for delaying or refusing a vaccine.

Another study by Glanz et al. investigated if children suffering from pertussis infection were more likely to have their parental refusal than those who did not develop pertussis infection [35]. The authors conducted a case-controlled study among children between 2 months to 18 years associated with the Kaiser Permanente Colorado (KPCO) health plan. Potential pediatric cases for pertussis were garnered using the KPCO medical database without prior knowledge of vaccination status. Confirmed pertussis cases were finalized if the medical chart verified a positive polymerase chain reaction (PCR) test or positive culture of B pertussis. Each case was provided an index date as the day pertussis was diagnosed and was matched to 4 randomly selected controls by gender, duration of KPCO enrollment and age at the index date and were considered for the primary analysis. The controls were selected from a group of pediatric people enrolled in the KPCO healthcare plan having no record of pertussis before the index date.

A medical abstractor reviewed the vaccination history of the children, unaware of the case status, labeled the children as ‘vaccine acceptors’ if they were
vaccinated at an appropriate age against pertussis at the index date. The same label was applied to children who were partially vaccinated against pertussis at index date. The objective behind lack of vaccination was not vaccine refusal. The children were labeled as ‘vaccine refusers’ if the medical chart explicitly documented the lack of vaccination was due to parental refusal.

Conditional logistic regression was applied to determine pertussis case status with the predictor being ‘vaccine refuser’ or ‘vaccine acceptor’. The matched odds from the conditional logistic regression model were used to compute the percentage of risk attributed to vaccine refusers and the total population. Some cases were not enrolled in KPCO healthcare during their primary 4-dose series of pertussis. Also, the study would be biased given the behavior of vaccine acceptors and refusers when exhibited to an acute illness of their children. Vaccine acceptors are more likely than vaccine refusers to get medical care for their children in the case of infection. Also, the physician’s decision to perform various tests might be influenced by the child’s vaccination status. Physicians are more likely to test children who are unvaccinated during the time of illness thus overestimating the association between vaccine refusers and pertussis infection.

To address the potential bias, secondary analysis for children between 2 to 20 months was conducted and was matched against 10 randomly sampled control cases. Laboratory confirmed cases and patients with a strong suspicion for pertussis were excluded from the study. The odds were calculated for vaccine acceptors and refusers for visiting a clinic for an upper respiratory infection (URI) and receiving a pertussis lab test at a URI-related clinic.

In all, 439 patients were identified for diagnosis for pertussis for primary analysis from the KPCO database with 41% of them verified for positive PCR or a positive culture for pertussis. For 11% of the verified cases, parents refused all pertussis immunizations. The control had a population of 595 children who were either unvaccinated or partially vaccinated against pertussis and belonged
to the same age group as the cases. Around 0.5% of the population of the control group had children whose parents refused one or more pertussis immunizations. The secondary analyses identified 748 children as continuously enrolled in the KPCO healthcare plan from 2 to 20 months. In this cohort, 13% of the cases and 0.7% of the control had their parents refusing to all pertussis immunization.

In the primary case-control analysis, vaccine refusal was strongly associated with laboratory-confirmed pertussis while pertussis infection accounted highly for secondary analysis further estimating that 11% of the pertussis cases were associated with vaccine refusal. The study concluded that vaccine refusers are at 23 times higher risk for pertussis as compared to vaccine acceptors thus reflecting a strong correlation between parental vaccine refusal and risk of pertussis infection in children.

Another study by Dube et al. sought to identify specific characteristics related to vaccine hesitancy at the global level [36]. They referred to ‘vaccine hesitancy’ as a delay in vaccine acceptance or refusal of a vaccine despite its availability. Data were collected from semi-structured interviews held by WHO Strategic Advisory Group of Experts (SAGE) from six WHO regions: Africa, America, Eastern Mediterranean, Europe, South-East Asia, and Western Pacific for three economic categories of low, medium and high-income countries. Interviews were completed by 13 Immunization managers (IM) with each interview lasting for approximately 30 minutes. Data were analyzed by questions and mapped against a matrix of determinants. IM’s debriefed on their understanding of vaccine hesitancy, the impact of vaccine hesitancy on countries’ immunization programs in terms of vaccine safety, acceptance and refusal. Four IM’s reported complacency of vaccination being an issue in their country while four IM’s stated that immunization was treated as utmost priority. Factors concerning convenience and ease of access to vaccination were noted as an important factor by nine IMs.
Determinants of vaccine hesitancy consisted of

i. Contextual influences such as religion, culture, gender, socioeconomic status, influential leaders and anti- or pro-vaccination lobbies, geographic barriers and communication and media environment,

ii. Individual and group influences such as risk or safety perceptions, level of trust in the health system and healthcare providers and lack of knowledge,

iii. Vaccine and vaccine-specific issues such as the introduction of a new vaccine, the design of vaccination program, reliability and source of vaccine, the role of a healthcare professional, vaccination cost and their risks and benefits.

The study revealed that discrepancy between interpretation of the term ‘vaccine hesitancy’ among IM’s indicated a lack of understanding. Some IM’s stated the impact of vaccine hesitancy on the immunization program to be a minor problem, mostly due to their misinterpretation of terminology. IM’s struggled to provide a rate of people for lack of confidence. Most IMs agreed that vaccine hesitancy is not restricted to specific communities but exists across all socioeconomic strata of the population. Two IM’s noted the health professional themselves to be vaccine-hesitant bringing to the concern that health professional knowledge and attitude has proven to be an important determinant of their own vaccine uptake, recommending the vaccine to a patient and vaccine uptakes of their patients. In conclusion, the determinants provided by the SAGE group fitted well within the matrix of determinants for vaccine hesitancy. Further studies illustrated that vaccine hesitancy is largely influenced by factors such as complacency, convenience and confidence and is context-specific, varying across time, place and type of vaccine [37].

In another study by Dube et al., the authors attempt to define vaccine hesitancy while examining the potential causes and determinants of the apparent increase of vaccine hesitancy in the world [38]. The study further analyzes the determinants of individuals’ decision-making capability for vaccination based
on pre-defined factors that are influential. The study framed a conceptual model comprising of three domains of factors that interact and lead to vaccine hesitancy at the individual level. The definition of vaccine hesitancy is itself ambiguous due to sociodemographic architecture.

Factors such as historical data e.g. past experiences, family history, political and socio-cultural context such as controversies are the most important causes for vaccine hesitancy in individuals. Public health, vaccine policies, the role of health professionals since they are a trusted source of information for most patients heavily affects individuals’ ability to take a stand for vaccination. Psychological factors influencing vaccine acceptance at an individual level were determined to be knowledge about vaccines, past experiences with vaccination services, perception towards importance of vaccination for maintaining health, health professionals’ recommendations and use of complementary or alternative medicines (CAM), risk perception, trust in health officials and policies, subjective norms, social pressure, social responsibility and moral or religious convictions.

Opel et al. developed a survey to accurately determine parental vaccine hesitancy [39]. The survey was developed by reviewing previous studies and premade surveys on parental health beliefs for vaccination. Additional themes were generated from focus groups and pediatricians creating a draft of the proposed survey. The survey was reviewed by six immunization experts ranking the items on the scale of 1-5 for the significance of lower to higher for predicting vaccine-hesitant parents while dropping items with the lowest third of the ranks.

The proposed survey focused on four domains: immunization behavior, beliefs about vaccine safety and efficacy, attitudes towards vaccine mandates and exemptions and trust. The initial survey contained seventeen items along with ten more from the focus group interviews resulting in 27 items where nine were deleted during revisions thus yielding a total of 18 items on the survey. The
resulting survey was presented to 25 parents for testing its validity, usability and item understandability. The authors yielded positive results for measuring attitudes for immunization.

2.6 Different emotions revolving around vaccine

Having thoroughly analyzed the public perception towards a vaccine, researchers proceeded to map these perceptions towards vaccination of acceptance, refusal, and hesitancy to specific emotions. A study by Casiday et al. determined the level of agreement for trust in medical authorities for MMR-accepting parents and MMR-refusing parents after the news MMR being linked to autism broke out [40]. The authors developed a questionnaire and presented it to 87 parents asking about their child’s year of birth and whether he/she received MMR or single measles, mumps, rubella vaccine, parents’ level of agreement with 20 statements related to vaccination, use of and information with satisfaction sources and respondent’s age, gender, occupation, level of education and total number of children with their age. A 4-level Likert scale varying from strongly disagree to strongly agree was provided to a question asking parents to ‘take a stand’ enabling to calculate the proportion between parents agreeing and disagreeing with each statement. Questions were phrased as both positively and negatively viewed towards MMR to measure a balance of views among parents. The survey was provided to children born between October 2000 and September 2002 enrolled in Primary Care Trust. Logistic regression evaluated the relationship between MMR acceptance and parental education, occupational class, the interaction between education and class, parental age and number of children.

Only 3.1% of the children had not received either of the vaccines while multivariate logistic regression determined the number of children being the only factor predicting MMR acceptance. As presumed, MMR refusing parents
less likely agreed with scientific attestation for a vaccine to be safe, although most vaccine accepting parents were ambivalent about the safety of the vaccine. Parents distinguished between ‘doctors’ and ‘my doctor’, thus conveying that a trusting relationship between them is far better than the medical authorities toward increasing patients’ trust in the information provided.

Another study by Marlow et al. constructed an association between general vaccine attitudes, trust in doctors, past experience with vaccination and acceptance of HPV vaccination [41]. The authors fashioned a questionnaire that was presented to mothers having at least one daughter within the age of 8-14 years. The survey items were adapted from previous research analyzing vaccination attitudes and trust in their doctors on a 4-point scale ranging from strongly disagree to strongly agree. Questions related to previous experience with vaccination asked about vaccine delay, refusal, the experience of side-effect or bad reaction and regret over vaccinating any of their children were measured as ‘yes’ or ‘no’. Mothers were then provided with an information sheet about HPV and its link with cervical cancer and were asked if they were likely to vaccinate their daughter sometime soon recording their response on a 5-point scale. Mothers agreeing to vaccinate against HPV were labeled as vaccine acceptors while those resuting it were labeled as vaccine non-acceptors. All the factors were evaluated for their contribution towards predicting intention to accept the HPV vaccine using Binary Logistic Regression.

The results reported 75% of mothers displaying positive response to vaccinating their daughters against HPV vaccination. Past experience and trust in doctors contributed significantly towards vaccine acceptance. The study also illustrates that educating a parent with the general importance of the vaccine and reassuring its safety might improve acceptance among parents.

While people trusting vaccines have credited their doctor for medical concerns, people harboring negative emotions towards vaccines accounted for con-
cerns regarding vaccine safety, side effects, and religious beliefs as their driving emotion. A study by Chapman et al. examines the role of worry and regret for accepting a flu shot, one of the most popular vaccines [42]. The authors acquired data from three surveys presented to faculty and staff from two universities in New Jersey offering free flu shots from Fall 2001 to Fall 2002. The surveys questioned their participants if they received a flu shot and their intention to receive a flu shot in the upcoming fall, along with perceived risk of likelihood of flu without a flu shot or with a flu shot and severity of flu without the flu shot and anticipated worry or regret if they were to get a flu shot or not and about getting flu or not. Responses to the survey were recorded on a 5-point Likert scale.

The finding of the study reported that perceived risk likelihood reduction and perceived risk severity were strong predictors of reducing anticipated worry and regret. To analyze if the participant receiving a flu shot in Fall 2001 is likely to vaccinate himself against flu in Fall 2002, the results directed that higher perceived risk severity and a larger reduction in risk likelihood, worry or regret resulting from vaccination amplified participant’s intention to vaccinate again. Discovering a correspondence between anticipated and experienced emotion for the flu shot, the results reported a discrepancy between both of them further supporting that vaccinators accepted less regret than anticipated, however experiencing more worry than anticipated while non-vaccinators experienced as much regret and worry as anticipated. This discrepancy between anticipated and experienced emotions did not drive the participant’s decision to get vaccinated in the subsequent year.

Analyzing the public attitude in terms of fear and concern, Watel et al. hypothesized that opposition to vaccination, in general, reflects one’s commitment to risk culture in risk society [43]. To demonstrate this, it assumes opposition to vaccination in general as ‘unfounded fear’ while opposition to the H1N1 vac-
cine as a ‘legitimate concern’. The authors conducted a telephone survey for people aged between 15-79 years. The authors selected participants for interviews based on their socio-demographic and socio-economic background such as gender, age, education level, household composition, and income. Overall 9480 people participated in the survey conducted between October 2009 to June 2010.

The participants were asked a question regarding their attitude towards vaccination if they favored certain vaccines and their immunization status for Hepatitis B and seasonal influenza. The results reported that attitudes towards vaccination in general and H1N1 varied significantly throughout the timespan of study though correlated strongly within a month’s sample. People aged between 50-64 and people with low education levels opposed all vaccines in general while people aged between 35-49, females, intermediate level of education and income opposed H1N1 vaccination. Multivariate analysis amongst the predictors stated that opposition to both kinds of vaccination is bidirectional, that is opposition to vaccination in general and H1N1 vaccination was a predictor of each other.
3 Purpose of the study

Given the in-depth analysis done by researchers, we devise a novel approach to categorize tweets as per public outlook towards vaccination and reveal public’s emotional valence to vaccine by harvesting Twitter data. In our study, we investigate the following research questions.

Research Question 1: To what extent is it feasible to build a classifier which can distinguish between relevant and non-relevant tweets related to vaccination?

Research Question 2: Using the topic modeling framework, what general themes exist in the corpus of the tweets collected?

Research Question 2.1: Considering Research Question 2, how many topics are necessary to describe the corpus of tweets?

Research Question 2.2: Considering Research Question 2, what similarities and dissimilarities do these topics exhibit?

Research Question 3: What is the plausibility of a classifier model to differentiate between tweeters supporting vaccine, tweeters who disprove of vaccine and tweeters who maintain a neutral stand towards vaccine?

Research Question 4: How does the public emotional response about vaccine change throughout the year?

Research Question 5: How do the emotions differ in people who support, reject or maintain a neutral view towards vaccination and how does that change throughout the year?
4 Methods

4.1 Data Preparation

This section lays the foundation for how the tweets were mined from Twitter and then prepared for machine learning algorithms.

4.1.1 Harvesting tweets

We used the R programming language to harvest tweets from Twitter. R is intended for statistical analysis and is an open-source software easily available across various platforms. We performed the analysis on the ‘twitteR’ package of R text analysis tools on RStudio. To extract tweets from Twitter, a Twitter application must be created to generate Consumer and Access keys and tokens. Once these credentials are verified by Twitter, the researcher is authorized to extract data. However, the Twitter Application Programming Interface (API) allows extracting only a small amount (around 1%) of the total volume of tweets. The tweets were collected based on a comprehensive keywords list which comprised of words related to vaccines or diseases corresponding to the vaccine as well as popular hashtags. The language for extracting tweets was restricted to English. For e.g. ‘vaccines’, ‘vaccination’, ‘flu’, ‘goodluck-withyourvaccine’, ‘saynotovaccine’, ‘Hepatitis A’ and ‘tetanus’. The keyword list consists of 78 keywords where some keywords were also a combination of words like ‘autism’ and ‘vaccine’ or ‘smallpox’ and ‘vaccine’, to extract more apt tweets. Information such as if the tweet is a retweet, number of times the tweet has been retweeted, the username of the person who tweeted, location of the person and the date the tweet was posted was also extracted and compiled.
in a comma-separated value file. We harvested tweets from February 11, 2018, to February 9, 2019. Approximately 8 million (7,917,334) tweets were compiled within the timespan of a year.

4.1.2 Double Filtration Process

Filter 1: Removing tweets not containing the keywords

One of the drawbacks while working with Twitter data is that Twitter APIs are restricted to extract only the first 140 characters of a tweet. Due to this, if the original tweet contains one of the keywords specified in the keyword list after 140 characters, the API will not extract the keyword thus making the tweet vague in turn rendering to be useless. To create an apt dataset, we designed a filter that removed tweets that did not include the words in the keyword list.

Filter 2: Removing duplicates

Many of the tweets are extracted multiple times, mostly because of being retweeted. Thus, we removed the retweeted notion ‘RT’ from the tweet, checked the tweet for duplication and deleted them consecutively. We then restored ‘RT’ into the tweet.

4.1.3 Annotation

Labeling a tweet or text based on some pre-specified criteria is referred to as annotation. This annotation is used by a machine learning model to classify text based on a given set of features. In our study, we built a 2-stage classifier model to classify:

1. if the tweet is relevant to vaccination or not
2. if the tweet is tweeted by a Pro-vaxer, Anti-vaxer or Unclear

The criteria for labeling the first classifier model were:

a. Label as ‘relevant’ if the tweet concludes to be about a vaccine-related topic or vaccine itself
b. Label as ‘irrelevant’ if the tweet contains the keyword, but doesn’t pertain to vaccination in a medical context

The criteria for labeling the second classifier model were:

a. Label as ‘Pro-vaxer’ or ‘Anti-vaxer’ only if it states the opinion of a person. If the tweet appears to be a news item or just a statement, then label it as ‘Neutral’ or ‘Unclear’

b. Label as ‘Pro-vaxer’ if the tweet shows the twitterer approves, believes in or supports vaccination or opposes ‘Anti-vaxer’

c. Label as ‘Anti-vaxer’ if the tweet shows that the twitterer denies or discredits vaccination or opposes ‘Pro-vaxer’

A random sample of 100 tweets was coded for each classifier by three annotators to assess agreement amongst the annotators.

4.1.4 Pre-processing

The tweets harvested using the Twitter API are crude in their core form. To implement machine learning algorithms for tweet classification, the tweets are required to be converted into a machine-readable format. This is achieved by cleaning the core tweets or pre-processing the tweets. The following chart delineates the pre-processing steps also called text elaboration applied to the model.
Figure 4.1: Text Elaboration
a. Conversion to ASCII
Some of the English letters are similar to Latin letters. We forced the tweets
to translate to ASCII, thus eliminating non-English letters if any.

b. Removal of URL, mentions, and hashtags
Twitterers tend to post hypertext links to redirect to a related topic or mention
(followed by @ sign) someone in a tweet to notify them about the topic. One
of the trending patterns is to add a hashtag (followed by pound key) which
emphasizes a certain topic. As these are not useful for text classification, we
removed them from the tweets.

c. Removal of special and control characters
Characters like horizontal tabs (\t), escape (esc), backspace (\b) and special
characters or symbols are removed from the tweets.

d. Removal of extra white spaces
Leading or trailing white spaces occurred while extracting tweets are removed.

e. Normalization
Tweets are converted to lower-case to remove ambiguity while creating a feature
matrix.

f. Stop words removal
Stop words are a set of commonly occurring words in English language: ‘the’,
‘I’, ‘me’. These words are removed as they can be non-informative and increase
memory overhead.

g. Stemming
English words contain prefixes and suffixes, which are converted to its root
form. For e.g. words ‘study’, ‘studies’ and ‘studying’ are converted to ‘studi’.
4.2 Feature Engineering

This section illustrates the methods implemented for each of the research questions mentioned in Section 2 and the evaluation metrics to validate the outcome. To address research questions 1 and 3, we implemented tokenization, vector space modeling, and latent semantic analysis.

4.2.1 Tokenization

To analyze any natural language data using machine learning algorithms, it is imperative to convert the human-readable text into a machine-readable format. This is achieved by deploying a method called tokenization. It is a process of segmenting texts into words or sentences. To segment the tweets into tokens, we implemented n-grams for deriving features for our model. N-grams are simply a sequence of ‘n’ words in a given text or document. Generating one token per word is labeled as unigrams, generating one token for two consecutive words is called as bigrams and so on. In our study, we generated unigrams and bi-grams for feature set.

Consider a tweet, “Thinking of skipping the flu shot this year. The flu shot is only 10% effective”. After pre-processing, the tweets become “thinking skipping flushot year flushot 10 effective”. The tokens generated from the tweet are as follows:

<table>
<thead>
<tr>
<th>Uni-grams</th>
<th>Bi-grams</th>
</tr>
</thead>
<tbody>
<tr>
<td>thinking</td>
<td>thinking_skipping</td>
</tr>
<tr>
<td>skipping</td>
<td>skipping_flushot</td>
</tr>
<tr>
<td>flushot</td>
<td>flushot_year</td>
</tr>
<tr>
<td>year</td>
<td>year_flushot</td>
</tr>
<tr>
<td>10</td>
<td>flushot_10</td>
</tr>
<tr>
<td>effective</td>
<td>10_effective</td>
</tr>
</tbody>
</table>

Table 4.1: Example of uni-grams and bi-grams

Once tokens are generated, it is feasible to create a document term matrix where for each tweet, the count of each token, if existed were tracked. The
document term matrix for the unigram features will be:

<table>
<thead>
<tr>
<th>features</th>
<th>thinking</th>
<th>skipping</th>
<th>flushot</th>
<th>year</th>
<th>10</th>
<th>effective</th>
</tr>
</thead>
<tbody>
<tr>
<td>document</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 4.2: Document term matrix of unigram features

Thus, each tweet or document is represented by a vector of numbers in our feature space model. This is also termed as a bag-of-words model.

N-grams allow us to preserve word ordering and thus augments the frequency matrix. This often leads to increased performance for machine learning models trained with more than just unigrams or the bag-of-words model.

While working with the bag-of-words model, each ‘t’ word or token in the training set is accounted as one feature. This leads to high sparsity as the feature space expands. Most of the features for a particular document will be empty or zero as ‘t’ word or token will not occur in that document thus introducing the problem of sparsity. This confines the feature space into two types: non-significant features and significant features whereas in the real world, some features might be more worth noting than the others. Furthermore, terms appearing frequently in documents are less likely to be significant. To assign significance to each word or ‘term’ in our feature space model, we calculated their weights using term-frequency inverse document frequency, abbreviated as tf-idf.

Mathematical representation of tf-idf:

\[
TF_{IDF}(t, d, D) = TF(t, d) \times IDF(t, D)
\]

where, t represents term d represents document D represents all the documents in the corpus
\[ TF(t, d) = \frac{freq(t, d)}{\sum_i freq(t_i, d)} \]

\[ IDF(t, D) = \log \frac{1 + |D|}{1 + df(d, t)} \]

where,

\( TF(t, d) \) is number of times the certain word or term ‘t’ appears in a tweet or document ‘d’

\( IDF(t, D) \) calculates the logarithm of the number of documents ‘d’ in the entire document or corpus ‘D’ divided by the number of documents where the term ‘t’ appears.

Thus, TF normalizes the term frequency across documents while IDF penalizes terms that shows up in every single document.

### 4.3 Vector Space Modeling

Even though by applying term frequency-inverse document frequency improved the bag-of-words and n-grams model by providing significance of each term, the feature space model remains sparse up to an extent pertaining to computability and scalability issues. This can be addressed by using the vector space model.

The objective of the vector space model is to treat each row in a document as a vector which is a collection of different term weights within the document. These vectors are then mapped into geometrical space to analyze if certain documents are more alike than others. This helps to understand the relationships between the documents.

Consider the following example:
Table 4.3: Example for Vector Space Model

<table>
<thead>
<tr>
<th>ABC</th>
<th>XYZ</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td>10</td>
<td>3</td>
</tr>
<tr>
<td>8</td>
<td>7</td>
</tr>
</tbody>
</table>

By mapping the coordinates of the documents, it can be inferred that Doc 1 is more similar to Doc 3 than Doc 2 and vice-versa. The dot product of vectors also surmises the similarity between the documents.

Dot product of:
- Doc 1 and Doc 2 = (6 * 10) + (10 * 3) = 90
- Doc 1 and Doc 3 = (6 * 8) + (10 * 7) = 118
- Doc 2 and Doc 3 = (10 * 8) + (3 * 7) = 101

It can be confirmed from the dot products of the documents that Doc 1 is more similar to Doc 3 than Doc 2, thus aligning to the geometric understanding. Applying matrix multiplication to all documents at once conserves computational time. The dot product of all documents can be computed by...
multiplying the matrix by its transpose.

$$\text{Dot product of all documents} = XX^T$$

The dot product of the documents is also indicative of document correlation for a given set of matrix terms.

## 4.4 Latent Semantic Analysis

Text data generally comprises of the large corpus after the preprocessing. Some of the words in data differing in context might preserve the same meaning. This can be achieved by applying the latent semantic analysis (LSA). LSA extracts relationships between the documents and terms assuming that terms that are close in meaning will appear in similar pieces of text. It provides insights into the corpus and is a useful tool while dealing with information retrieval tasks. It is suitable for filtering out noise features in the data and represents data in a simpler form.

LSA leverages linear algebra technique called singular value decomposition (SVD) factorization of a document matrix to extract these relationships. The purpose of SVD is to decompose a matrix into smaller pieces.

LSA deduces a lower-dimensional representation of vectors from high dimensional space. The input into the LSA model is a term-document matrix that is generated from the corpus using n-grams, where each column corresponds to the document and each row corresponds to terms. SVD then factorizes this matrix into three matrices: the first matrix expresses topics in regard to documents, the second matrix expresses topics in regard to terms and the third matrix contains the importance for each topic. In mathematical terms, it can be represented as

$$\text{SVD of } X = U \sum V^T$$

42
where,

$U$ is eigenvectors of term correlations i.e. $XX^T$

$V$ is eigenvectors of document correlations i.e. $X^TX$

$$\sum$$ represents the sum of the singular values of the factorization.

Term correlations and document correlations provide a higher and abstract level of signals from semantic correlations.

LSA often remediates the curse of dimensionality problem as the matrix factorization has the effect of combining columns or terms, potentially enriching signal data. Thus, by selecting a fraction of the most important singular values, LSA can dramatically reduce dimensionality. However, SVD factorization is computationally intensive and reduced factorized matrices are approximations thus providing minimal loss of precision.

Mathematically, the closeness between two document vectors can be measured by calculating the cosine angle between them. The cosine between two document vectors is always measured between 0 to 1 where 1 signifies that the documents are perfectly similar and 0 means the document vectors are orthogonal and are dissimilar. The cosine angle between Doc 1 and Doc 2 can be calculated as

$$\cos \theta = \frac{Doc1.Doc2}{lengthofDoc1 \times lengthofDoc2}$$

Thus, whenever a new query term vector is introduced into the corpus, the cosine between the query term vector and each document vector is computed. Whichever document holds high similarity scores is considered as a relevant document to the query term.

To access the reliability of agreement between raters, statistical measures
such as Fleiss kappa [54], Pearson Correlation [55] and Cronbach’s alpha [56] were implemented which measures the rate between 0 signifying for poor agreement to 1 signifying perfect agreement. We also calculated percentage agreement amongst the raters.

Confusion Matrix:

The confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. It is a ‘quick reference guide’ to summarize your model. The table consists of four different combinations of predicted and actual values.

We derived accuracy, sensitivity, specificity, F-score, and area under the curve from the confusion matrix. The accuracy of the model is estimated by computing the ratio of correct predictions to total predictions made. Sensitivity also termed as true positive rate or recall, measures the proportion of actual positives that are correctly identified. Specificity, also termed as a true negative rate, measures the proportion of actual negatives that are correctly identified. F-score is a weighted average of the true positive rate i.e. recall and precision. A receiver operator characteristic (ROC) curve is most commonly used to visualize
the performance of a binary classifier and Area under the curve (AUC) is the best way to summarize its performance in a single number [85].

4.5 Topic Modeling

Topic Modeling is a type of statistical model to identify abstract topics occurring within the set of documents. The model scans a collection of documents or corpus, examines how words and phrases co-occur within the corpus and automatically learns groups or clusters of words that best characterize those documents. These collective words can often appear to represent a coherent theme or topic. It also helps to analyze hidden patterns that are present across the collection of documents. Latent Dirichlet allocation (LDA) is a common method of topic modeling [44].

LDA is a generative probabilistic model for the collection of text data or corpus. It is a form of unsupervised learning that views documents as a bag of words where its order does not matter. LDA works by first making a key assumption of setting a number of topics for the corpus and assigns a set of words to those topics. The functioning of LDA for each document m is specified as below:
1. Assume there are k number of topics across all documents.

2. Distribute these k topics across document m (this distribution is known as $\alpha$) by assigning each word a topic.

3. For each word w in document m, assume its topic is wrong but every other word is assigned to correct topic.

4. Probabilistically assign word w a topic based on two things:
   
   a. what topics are in document m
   
   b. how many times word w has been assigned a particular topic across all of the documents (this distribution is known as $\beta$)

5. Repeat this process a number of times for each document.

Figure 4.5: Plate notation of LDA

Above is the plate notation of LDA which is usually used to represent probabilistic graphical models. Here,

$\alpha$ is the per-document topic distribution

$\beta$ is the per-topic word distribution
\( \theta \) is the topic distribution for document \( m \)

\( \phi \) is the word distribution for topic \( k \)

\( Z \) is the topic for \( n^{th} \) word in document \( m \)

\( W \) is the specific word

In the plate model diagram of LDA above, \( w \) is grayed out as it is the only observable variable in the system while others are latent. \( \alpha \) is a matrix where each row is a document and each column represents a topic. A value in row \( i \) and column \( j \) represents how likely document \( i \) contains topic \( j \). A symmetric distribution would mean that each topic is evenly distributed throughout the document while an asymmetric distribution favors certain topics over others. \( \beta \) is a matrix where each row represents a topic and each column represents a word. A value in row \( i \) and column \( j \) represents how likely that topic \( i \) contains word \( j \). Usually, each word is distributed evenly throughout the topic such that no topic is biased towards certain words.

Simply noting, a lower \( \alpha \) value places more weight on having each document composed of only a few dominant topics while a higher \( \alpha \) value will return many more relatively dominant topics. Similarly, a lower \( \beta \) value places more weight on having each topic composed of only a few dominant words.

The output of the LDA model yields a mixture of topics that contains words along with the likelihood that the given word will be used in conjunction with the given topic. The theme or topic is interpreted by the user by analyzing the top ‘\( n \)’ probability words for a given topic.

Since LDA is an unsupervised model, in order to finalize a sensible number of topics, perplexity measure, and Akaike’s information criterion (AIC) is used. Perplexity is a statistical measure of how well a probability model predicts a sample. As applied to LDA, for a given value of \( k \), estimate the LDA model.
However, the statistic is somewhat meaningless on its own. The benefit of this statistic comes in comparing perplexity across different models with varying $k$’s. The model with the lowest perplexity is considered as the best.

As noted previously, LDA, being an unsupervised model, functions on the user input $k$ as the number of topics. Estimating the appropriate number of topics is an important part of model selection. Studies note that choosing a large $k$ leads to deterioration of the learning rate, significantly increasing the computational cost of inference of the LDA model [52]. AIC is a statistic based on in-sample fit to estimate the likelihood of a model to predict or estimate the future values [53]. AIC provides an estimation of the model quality relative to the other models by estimating the loss of information while trading off between goodness of fit and the simplicity of the model.

Once the number of topics is finalized, the LDA model then assesses the underlying structure of the words within the data and attempts to find the group of words that best fits the corpus. The output table of the LDA model consists of the term-topic matrix, which breaks topics down in terms of their word components and the document-topic matrix, which describes the documents in terms of their topics. A word may be assigned to a single topic or multiple topics in varying proportions.

The term-topic matrix provides terms or words appearing in each topic and its weight on the topic. The weight of the term is indicative of how much the term ‘belongs’ to the topic. Due to the enormous size of the corpus, these words are sorted based on their weights. The top ‘n’ words are selected to interpret the topic.

4.6 Calculating emotion and sentiment scores

Various lexicon-based methods are available to elicit emotions pertaining to a particular text. NRC Word-Emotion Association Lexicon aka EmoLex is
a popular method comprising of a list of English words and their associations with eight basic emotions: anger, anticipation, fear, trust, disgust, surprise, sadness, joy and two sentiments: positive and negative [86]. The presence of an emotion-associated word adds the emotion by one point. Thus, a score of 0 for an emotion represents the tweet does not exhibit the emotion. The list consists of 14182 unigrams and around 25000 senses related to those words. The average of the responses of each emotion derived through EmoLex throughout the year can be utilized to analyze the transition of emotional response.

4.7 Analysis of Emotion and Sentiment

Multivariate analysis of variance (MANOVA) is simply an extension of analysis of variance (ANOVA). In ANOVA, the statistical difference on one continuous dependent variable is examined by an independent grouping variable while MANOVA extends this analysis by considering multiple continuous dependent variables together into a weighted linear combination or composite variable. In simple words, MANOVA deals with two or more dependent variables simultaneously. MANOVA benefits over several separate ANOVAs as it takes into account correlations between dependent variables which results in richer use of the information in the data.

An ANOVA assumes two possible cases or statements, called as hypothesis. The two-hypothesis examined by the ANOVA are null hypothesis and alternate hypothesis. The null hypothesis assumes that all the sample means are equal, or the factor did not have any significant effect on the results. Whereas, the alternate hypothesis states that at least one of the sample means is different from another.

To test the assumptions of ANOVA, F-ratio and associated probability value (p-value) are calculated. The statistic which measures if the means of different samples are significantly different or not is called the F-Ratio [103].
Lower F-ratio concludes in similar sample means; thus, a null hypothesis cannot be rejected. P-value is the probability of obtaining a result at least as extreme, given that null hypothesis is true.

The significance level, also denoted as alpha or \( \alpha \), is a predefined probability of rejecting the null hypothesis when it is true. If a p-value associated with the F-ratio is smaller than the significance level, then the null hypothesis is rejected, and the alternative hypothesis is supported. Once the null hypothesis is rejected, post hoc tests are performed to examine which groups are different from each other. Due to the large sample size, the significance level for the test was determined to be 0.01.

Clinical significance is the practical importance of a treatment effect - whether it has a real genuine, palpable, noticeable effect on daily life [99]. A study that claims clinical relevance may lack sufficient statistical significance to make a meaningful statement. Conversely, a study that shows a statistically significant difference in two treatment options may lack practicality [100]. The results of a study can be statistically significant but still be too small to be of any practical value.

To determine the practical importance or clinical significance of the study, the effect size is taken into account. The effect size is a quantitative measure of the magnitude of an effect. Partial eta squared is a common measure to estimate an effect size by ANOVA. The partial eta square for the clinical significance was determined to be 0.01 [104].
5 Results

This section describes the data distribution and the results of the classifier model. Topic modeling was performed, and the outcome was interpreted in the form of social norms.

5.1 Data Distribution

Approximately 2.5 million unique tweets were identified in the dataset after being applied through all preprocessing steps and duplication removal. The further steps for classification and results were performed on this dataset.

![Figure 5.1: Frequency of tweets collected from February 2018 to January 2019 (Total tweets = 7,917,335, Relevant Tweets = 1,898,067)](image-url)
5.2 Performance of relevancy classifier

Research Question 1: To what extent is it feasible to build a classifier which can distinguish between relevant and non-relevant tweets related to vaccination?

Inter-rater Reliability Scores

Three annotators with expertise in biology and and knowledgeable about vaccination coded a random sample of 100 tweets. Discrepancies were resolved by discussion and tweets were recoded by the annotators. The results of the agreement between each annotator are shown in Table 5.1.

<table>
<thead>
<tr>
<th></th>
<th>Fleiss Kappa</th>
<th>Pearson Correlation</th>
<th>Cronbach’s Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rater 1 and Rater 2</td>
<td>0.74</td>
<td>0.75</td>
<td>0.86</td>
</tr>
<tr>
<td>Rater 2 and Rater 3</td>
<td>0.63</td>
<td>0.65</td>
<td>0.78</td>
</tr>
<tr>
<td>Rater 1 and Rater 3</td>
<td>0.51</td>
<td>0.55</td>
<td>0.70</td>
</tr>
</tbody>
</table>

Table 5.1: Agreement between annotators for relevancy classifier

The percentage agreement between Rater 1 and Rater 2 was 87%, Rater 2 and Rater 3 was 82% and Rater 1 and Rater 3 was 75%. Fleiss kappa between Rater 1 - Rater 2 and Rater 2 – Rater 3 depicts an inter-rater reliability score above 0.6 which accounts for substantial agreement among the annotators. However, the score between Rater 1 and Rater 3 accounts for moderate agreement, it is bolstered by Cronbach’s alpha score of 0.70 specifying that the annotations from any rater can still be held valid.

Model Performance

A sample of 1000 tweets from each month between February 2018 to July 2018 was taken for a training set while 1000 tweets from August 2018 to January 2019 were taken for testing. Per best practices, we leveraged cross-validation as the basis of our modeling process. Using cross validation, we created estimates of how well our model will do in production of new, unseen data. Cross validation is powerful technique for assessing the effectiveness of the model, but
the downside is that it requires more processing. Thus, 10-fold cross-validation was applied to the training dataset and validated. We generated three types of features for our model: uni-grams (consists of one word per feature), bi-grams (consists of two consecutive words per feature) and unified-grams (unification of unigram and bi-grams). LSA was applied to each set of features to extract newly refined features from the old feature set.

**LSA Components**

Even though articles specify that 300 is the best number of features to extract all meaningful relationships from the data, given the wide range of textual data available, we extracted the different number of components from the feature set to evaluate the best number of features and test it across the best performing classifier. Following is the performance of the different number of components trained on the dataset using 10-fold cross-validation and tested on unseen data using best performing classifier.

<table>
<thead>
<tr>
<th>Components</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>300</td>
<td>90.45</td>
</tr>
<tr>
<td>200</td>
<td>90.71</td>
</tr>
<tr>
<td>100</td>
<td>91.34</td>
</tr>
<tr>
<td>50</td>
<td>64.27</td>
</tr>
<tr>
<td>20</td>
<td>64.72</td>
</tr>
<tr>
<td>5</td>
<td>64.72</td>
</tr>
<tr>
<td>2</td>
<td>64.72</td>
</tr>
<tr>
<td>1</td>
<td>64.74</td>
</tr>
</tbody>
</table>

Table 5.2: Performance for different numbers of LSA components

Even though the features with 200 components and 100 components perform slightly better than 300 components, the improvement is not substantial. None the less, we extracted 200 features and 100 features both separately in the training set, anticipating it might perform better for upcoming data. However, the accuracy rate for the test data was less than the accuracy rate for 300 components analyzed for trend as shown in Figure 11. Thus, 300 components were determined to be used for the analysis. Furthermore, researchers have
also demonstrated that 300 components usually provide the best results with
documents of the size of hundreds of thousands [45].

![Figure 5.2: Performance of LSA components over time](image)

After extracting features from LSA, the new three feature set (unigrams, bi-grams and unified-grams) was trained on varied supervised machine learning algorithms as a base model consisting of only 300 components from LSA, an additive model consisting of base model features along with cosine similarity for each tweet or document and a test model consisting of unseen data. Features for the test model were mapped as per the training model. The performance of each classifier is presented in terms of accuracy below.

It can be demonstrated from the Table 5.3 that the additive model performed better as compared to the base model, thus indicating that the similarity between the documents played a crucial role while classifying the tweets. While analyzing which features are important for the best model, the feature 'similarity' was the topmost feature among the first 20 top features.
<table>
<thead>
<tr>
<th>Model name</th>
<th>Model type</th>
<th>unified-grams</th>
<th>bi-grams</th>
<th>uni-grams</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forest</td>
<td>Base model</td>
<td>90.03</td>
<td>76.38</td>
<td>74.9</td>
</tr>
<tr>
<td></td>
<td>Additive model</td>
<td>90.16</td>
<td>76.94</td>
<td>73.4</td>
</tr>
<tr>
<td></td>
<td>Test</td>
<td>90.45</td>
<td>69.89</td>
<td>72.4</td>
</tr>
<tr>
<td>knn</td>
<td>Base model</td>
<td>77.57</td>
<td>72.96</td>
<td>74.18</td>
</tr>
<tr>
<td></td>
<td>Additive model</td>
<td>61.91</td>
<td>61.36</td>
<td>62.80</td>
</tr>
<tr>
<td></td>
<td>Test</td>
<td>61.5</td>
<td>60.73</td>
<td>64.33</td>
</tr>
<tr>
<td>Neural Net</td>
<td>Base model</td>
<td>89.03</td>
<td>74.41</td>
<td>88.74</td>
</tr>
<tr>
<td></td>
<td>Additive model</td>
<td>88.88</td>
<td>74.41</td>
<td>88.74</td>
</tr>
<tr>
<td></td>
<td>Test</td>
<td>90.84</td>
<td>73.4</td>
<td>91.01</td>
</tr>
<tr>
<td>CART</td>
<td>Base model</td>
<td>83.31</td>
<td>71.55</td>
<td>82.40</td>
</tr>
<tr>
<td></td>
<td>Additive model</td>
<td>84.99</td>
<td>75.49</td>
<td>85.33</td>
</tr>
<tr>
<td></td>
<td>Test</td>
<td>61.11</td>
<td>64.75</td>
<td>35.25</td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>Base model</td>
<td>72.28</td>
<td>40.26</td>
<td>75.58</td>
</tr>
<tr>
<td></td>
<td>Additive model</td>
<td>72.88</td>
<td>40.26</td>
<td>78.32</td>
</tr>
<tr>
<td></td>
<td>Test</td>
<td>38.33</td>
<td>49.34</td>
<td>78.93</td>
</tr>
</tbody>
</table>

Table 5.3: Performance of relevancy classifier in terms of accuracy

Also, the table shows that the unified-gram model provides the best classification rate when compared with the bi-grams model and unigrams model thus specifying that features consisting of both unigrams and bi-grams make more robust classifications than dealt with alone. However, when the data were used to train the naive Bayes classifier, the performance seems to be in rapport with the other classifiers when tested using 10-fold cross-validation. But when the same classifier was tested against new data for unified-grams and bi-grams model, the performance seems to have dropped drastically.

It can be configured from the above table that the neural network model with unified-grams outperformed all other classifiers. To perceive the performance of the classifier on test data, we performed trend analysis. The outcome of the trend analysis for the relevancy classifier is shown. Figure 6.3 delineates the performance of the classifier over the given time period as a line chart to display the trend over time.

From here, we can say that since neural network using unified-grams is the best performing model in terms of accuracy and computational power. We used
this model to classify 2.5 million tweets by incorporating the relevancy classifier to acquire relevant tweets for further annotation. Using this, we yielded approximately 1.9 million tweets to be relevant to vaccination. Thus, the classifier classified 80% of the harnessed data as relevant tweets for our study.

5.3 Underlying themes in tweets for vaccination

Research Question 2: Using the topic modeling framework, what general themes exist in the corpus of the tweets collected?

To identify early clues from the text embedded in our tweets, we created a word cloud of the top 100 words frequently appearing in our dataset after removing the stopwords and the word ‘vaccine’ from the corpus. Word clouds also called a text cloud or a tag cloud, is an image composed of words in a corpus, in which the size of each word indicates its frequency or importance. So, the more often specific words appear in the corpus or text data, the bigger and bolder it appears in the word cloud.

Figure 6.4 indicates that the data weighs heavily upon the terms ‘get’,
‘flu’, ‘measl’, ‘rabi’ and ‘hpv’ suggesting that tweets in our data might be more related to topics of getting vaccinated for these diseases. Words such as ‘need’, ‘studi’, ‘think’, ‘know’, ‘cause’ and ‘affect’, ‘research’ gives the notion of commonly expressed concerns about efficacy and requirement of vaccines. Presence of disease-related terms such ‘flu’,‘hpv’, ‘hepat’, ‘mmr’, ‘measll’, ‘rabi’, ‘cancer’, ‘mening’ and ‘influenza’ depicts that these are the hot topics for discussions related to vaccination. The appearance of verbs such as ‘dont’, ‘risk’, ‘believe’, ‘never’ and ‘didnt’ are indicative of anti-vaxer tweets in the data.

Research Question 2.1: Considering Research Question 2, how many topics are necessary to describe the corpus of tweets?

The classified 1.9 million relevant tweets were modeled on the unsupervised learning method of LDA to discover the pattern or underlying theme in the dataset. To set an outcome as the number of topics in the dataset, we modeled all the procured relevant tweets from 2 topics to 100 and their perplexity scores were gathered. We also estimated AIC scores for these parameters to validate the topic count generated by LDA. The results for perplexity scores and AIC
scores from 2 to 10 topics have been graphed in Figure 6.5

Figure 5.5: Perplexity and AIC scores from 2 to 10 topics

The perplexity score and AIC score increases as the number of topic increases. Therefore, two topics were finalized as the best number of themes or topics defining the dataset.

Research Question 2.2: Considering Research Question 2, what similarities and dissimilarities do these topics exhibit?

Since the outcome of LDA analysis comprises terms along with their probability scores (beta), we extracted the top 100 terms from both topics based on their probability scores to delineate the topic.

From Figure 6.6, it can be seen that Topic 1 focuses primarily on people in general with the terms appearing in the word cloud are ‘peopl’, ‘children’, ‘kid’, ‘antivaxx’, ‘doctor’ and ‘parent’ and diseases such as ‘measle’, ‘polio’ and ‘flushot’. Some causation terms can also be seen in the word cloud such as ‘dont’, ‘cause’, ‘confirm’, ‘death’, ‘danger’ and ‘feel’. Topic 1 consists of 36
Figure 5.6: Word cloud for Topic 1: consequences of vaccination/non-vaccination

Figure 5.7: Word cloud for Topic 2: promotion of vaccination/non-vaccination

nouns, 54 verbs, 8 adjectives and 2 adverbs. The combination of nouns and verbs in the word cloud is indicative of hot trending topics. For example, nouns
‘cause’ suggests that recent measles outbreak in the United States, the state of
New York, New York City, and New Jersey are frequently discussed on Twitter
during the time period of data collection.

The word cloud for terms focusing on Topic 2 is depicted in Figure 6.7. Terms in
this topic comprise vaccine-preventable diseases such as ‘rabi’, ‘mening’,
‘cancer’, ‘hepat’ and ‘influenza’ along with cautionary terms usually associated
with them such as ‘infect’, ‘effect’, ‘need’, ‘risk’, ‘prevent’ and ‘risk’. Topic 2
consists of 50 nouns, 41 verbs, and 9 adjectives. While analyzing the terms in
the topic, we see that more nouns are present in Topic 2 than Topic 1. The
nouns appearing in Topic 2 are different than Topic 1 as well. By inspect-
ing some of the nouns such as ‘rabi’, ‘cancer’, ‘mening’, ‘health’, ‘disease’ and
‘research’ and verbs such as ‘risk’, ‘infect’, ‘test’, ‘infect’ and ‘studi’, we can con-
clude that Topic 2 focuses on the results of analysis of experiments conducted
on these diseases and its presentation to the public.

To get a better interpretation of the differences between the themes, we
also traced the dissimilar terms in the top 100 terms from both topics as shown
in Figure 6.8.

The terms in Topic 1 are more related to the effects of vaccination or de-
clining them such as ‘measl’, ‘people’, ‘don’t’ and ‘outbreak’. This implies that
Topic 1 is more associated with tweets like measles outbreak, polio vaccination
in children and the position of antivax committees. Terms in Topic 2 are mostly
associated with vaccine-related diseases such as ‘rabi’, ‘cancer’ and ‘hepat’, in-
spection terms such as ‘research’, ‘develop’ and ‘test’ and administration terms
such as ‘clinic’, ‘patient’ and ‘help’. This suggests that Topic 2 leans towards
marketing strategies for vaccination like getting the flu shot during flu season,
news about recent developments in studies of vaccination or their risk.
By inspecting the words in the word cloud for both topics and the dis-
similar terms among them, we can conclude that Topic 1 is associated with
the ‘consequences of vaccination’ and Topic 2 is associated with ‘promotion of
agendas related to vaccination (or non-vaccination)’.

5.4 Performance of perception classifier

Research Question 3: What is the plausibility of a classifier model to dif-
ferentiate between tweeters supporting vaccine, tweeters who disprove of vaccine
and tweeters who maintain a neutral stand towards vaccine?

For our study, we called upon the NRC sentiment dictionary to calculate
the presence of eight different emotions and their corresponding valence for
the text document. The emotions featured by the dictionary are anger, an-
ticipation, disgust, fear, joy, sadness, surprise and trust. We also determined
the polarity of the text by providing two emotion types based on these eight
emotions. These 10 features were also modeled in the classifier for perception
about vaccination.
Perception classifier

Understanding public outlook regarding vaccines is an imperative part of the study. Given the broad field of vision, we narrowed down our study to analyze public opinion into three categories: Pro-vaxer, Anti-vaxer and Neutral. Pro-vaxer is referred to the tweet conveying positive attitude towards a vaccine, supporting scientific facts and theories pertaining towards vaccine acceptance or refuting any concern or critic towards vaccine acceptance. Anti-vaxer is referred to the tweet apprehensive towards vaccine acceptance, expressing discomfort regarding scientific views or disagreement with facts related to advancement in social existence due to vaccine. Tweets not falling in any of the two categories or is dubious to comprehend are categorized as Neutral.

Inter-rater Reliability Scores

Annotators who coded tweets for the relevancy classifier also coded tweets for Pro-vaxer, Anti-vaxer and Neutral. The following table outlines that there was substantial agreement among the annotators.

<table>
<thead>
<tr>
<th></th>
<th>Fleiss Kappa</th>
<th>Pearson Correlation</th>
<th>Cronbach’s Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rater 1 and Rater 2</td>
<td>0.75</td>
<td>0.76</td>
<td>0.87</td>
</tr>
<tr>
<td>Rater 2 and Rater 3</td>
<td>0.63</td>
<td>0.65</td>
<td>0.78</td>
</tr>
<tr>
<td>Rater 1 and Rater 3</td>
<td>0.61</td>
<td>0.63</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Table 5.4: Inter-rater reliability scores for annotators for the perception classifier

Model Performance

LSA was implemented to extract 300 features from the corpus as a base model. To gain robustness, three different sets of auxiliary features were added in combination with each other. These three sets of auxiliary features are: 1. Eight emotions derived from tweets using NRC sentiment dictionary, 2. Two sentiments extracted from tweets using the NRC sentiment dictionary, and 3. Two topics featured by LDA. Table 5.5 shows the results of how these three sets of features perform when added in the model. Since the unified-grams neural
network model outperformed all other classifiers for the relevancy classifier, we used the same model to analyze the performance of the dataset. 10-fold cross-validation was used on the training set to analyze the outcome of the model.

<table>
<thead>
<tr>
<th>Model no.</th>
<th>LSA components</th>
<th>Emotions (8)</th>
<th>Sentiment (2)</th>
<th>Topic (2)</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>✓</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>56.68%</td>
</tr>
<tr>
<td>II</td>
<td>✓</td>
<td>✓</td>
<td>x</td>
<td>x</td>
<td>66.81%</td>
</tr>
<tr>
<td>III</td>
<td>✓</td>
<td>x</td>
<td>x</td>
<td>✓</td>
<td>66.81%</td>
</tr>
<tr>
<td>IV</td>
<td>✓</td>
<td>x</td>
<td>✓</td>
<td>x</td>
<td>66.06%</td>
</tr>
<tr>
<td>V</td>
<td>✓</td>
<td>✓</td>
<td>x</td>
<td>✓</td>
<td>66.10%</td>
</tr>
<tr>
<td>VI</td>
<td>✓</td>
<td>✓</td>
<td>x</td>
<td>✓</td>
<td>66.44%</td>
</tr>
<tr>
<td>VII</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>x</td>
<td>66.33%</td>
</tr>
<tr>
<td>VIII</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>66.77%</td>
</tr>
</tbody>
</table>

✓ denotes the set of features included while x denotes the set of features excluded

Table 5.5: Performance of different models in terms of accuracy

It can be seen from Table 5.7 that the model which does not include any of the three features sets i.e. the base model, provides lowest accuracy score while adding even a single feature set boosts accuracy by almost 10%. However, the model is not significantly affected by excluding or including any particular feature set in the model. This was cross-verified by modeling the dataset using random forest as well. The confusion matrix along with AUC, F1-score, sensitivity, and specificity for the model were also reported for gaining a better insight into how well the models perform.

<table>
<thead>
<tr>
<th>Reference ↓</th>
<th>Neutral</th>
<th>Pro-vaxer</th>
<th>Anti-vaxer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neutral</td>
<td>2962</td>
<td>247</td>
<td>124</td>
</tr>
<tr>
<td>Pro-vaxer</td>
<td>894</td>
<td>640</td>
<td>67</td>
</tr>
<tr>
<td>Anti-vaxer</td>
<td>565</td>
<td>97</td>
<td>404</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>0.67</td>
<td>0.65</td>
<td>0.68</td>
</tr>
<tr>
<td>Specificity</td>
<td>0.76</td>
<td>0.80</td>
<td>0.88</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>AUC</th>
<th>F1-score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.79</td>
<td>0.58</td>
</tr>
</tbody>
</table>

Table 5.6: Classification results for Model VIII trained with neural network

As seen in the confusion matrix, most of the tweets were classified correctly.
However, more than half of the tweets were misclassified as Neutral. This is due to the tweets which are incomplete in nature and are difficult to catch by a machine as the machine itself is unaware of the partialness of the tweet. When focused on Pro-vaxer and Anti-vaxer tweets, the misclassification rate is notably smaller between them. It is a positive indication for the model to be performing correctly.

For the training dataset in our model, we again garnered a sample of 1000 tweets from each month between February-2018 to July-2018 and tested it on the next six months i.e. from August-2018 to January-2019. 10-fold cross-validation was implemented on the training dataset. The results for test data are tabulated below.

Figure 5.9: Trendline for perception classifier for unseen data from August 2018 to January 2019

Figure 6.9 depicts the trend analysis for the perception classifier trained on tweets harvested from the first six months of data collection.
Now, 1.9 million tweets were classified using the unified-grams model trained on neural network. The result of the classifier is shown in Figure 6.10.

![Pie-chart of tweets classified as Pro-vaxer, Anti-vaxer and Neutral](image)

Figure 5.10: Pie-chart of tweets classified as Pro-vaxer, Anti-vaxer and Neutral

Tweets from the above classifier were noted according to the topics to verify the two topics stated.
<table>
<thead>
<tr>
<th>Tweets</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>The CDC reports that the vaccine available is only 23%-33% effective.</td>
<td>Neutral</td>
</tr>
<tr>
<td>CDC states that most private insurers cover #pneumococcal vaccine; it is also covered by Medicare B.</td>
<td>Neutral</td>
</tr>
<tr>
<td>RT @QldGreens: That time Barnaby Joyce argued against a national cervical cancer vaccine on the grounds it could make young women promiscuo</td>
<td>Neutral</td>
</tr>
<tr>
<td>YOU WON’T BELIEVE WHAT THEY ADMITTED ABOUT THE #FLU #VACCINE ON THE NEWS IN 1971... 60 Lab Studies Now Confirm</td>
<td>Neutral</td>
</tr>
<tr>
<td>So this woman didn’t die because she could afford the vaccine. Yes or no will suffice.</td>
<td>Neutral</td>
</tr>
<tr>
<td>@brandi_love @girlswaynetwork Japanese drug breakthrough. Kills flu virus in one day. Not a vaccine.</td>
<td>Neutral</td>
</tr>
<tr>
<td>Safety of #liveattenuated #MMR and #zoster #vaccines in multiple #myeloma patients on maintenance #lenalidomide or</td>
<td>Neutral</td>
</tr>
<tr>
<td>National Immunization Campaigns with Oral Polio Vaccine Reduce All-Cause Mortality: A Natural Experiment within Sev</td>
<td>Pro</td>
</tr>
<tr>
<td>No, the science is NOT ”still out”. There IS NO LINK between vaccines and autism. This woman is a disgrace</td>
<td>Pro</td>
</tr>
<tr>
<td>@WPTV We have plenty of science as to what happens when you dont get the vaccine and end up with the Black Plague.</td>
<td>Pro</td>
</tr>
<tr>
<td>Cancer vaccine eliminates all traces of #cancer in mice #Sustainability #Science #Medicine #Oncology #Genetics</td>
<td>Pro</td>
</tr>
<tr>
<td>(Reuters Health) Flu shots may be especially important for older women who are socially active, a study from Japan</td>
<td>Pro</td>
</tr>
</tbody>
</table>
In what scenario would withholding a vaccine from a child make sense to where you’d rather risk them getting POLIO

@futurism Ummm… He’s famously anti-vaccine. WTF are you doing sharing his thoughts on science?

Milwaukee interim health commissioner: ‘Science is still out’ on vaccines and autism:

I’m looking for examples of bad science advice- antivaccine, climate science denial…. anything else?

RT @MaryShew: Flu Vaccine Increases Your Risk of Infecting Others by 6-Fold, Study Suggests

RT @OnlyTruthReign: FORCED VACCINE STERILIZED 500,000 WOMEN and CHILDREN! NWO ’Sterilization E...

Raila Odinga: The government is injecting women with a vaccine that causes infertility

@realCharter DO NOT get the vaccine!!! That’s what’s killing people!

<table>
<thead>
<tr>
<th>Tweet</th>
<th>Opinion</th>
</tr>
</thead>
<tbody>
<tr>
<td>In what scenario would withholding a vaccine from a child make sense to where you’d rather risk them getting POLIO</td>
<td>Pro</td>
</tr>
<tr>
<td>@futurism Ummm… He’s famously anti-vaccine. WTF are you doing sharing his thoughts on science?</td>
<td>Pro</td>
</tr>
<tr>
<td>Milwaukee interim health commissioner: ‘Science is still out’ on vaccines and autism:</td>
<td>Anti</td>
</tr>
<tr>
<td>I’m looking for examples of bad science advice- antivaccine, climate science denial…. anything else?</td>
<td>Anti</td>
</tr>
<tr>
<td>RT @MaryShew: Flu Vaccine Increases Your Risk of Infecting Others by 6-Fold, Study Suggests</td>
<td>Anti</td>
</tr>
<tr>
<td>RT @OnlyTruthReign: FORCED VACCINE STERILIZED 500,000 WOMEN and CHILDREN! NWO ’Sterilization E...</td>
<td>Anti</td>
</tr>
<tr>
<td>Raila Odinga: The government is injecting women with a vaccine that causes infertility</td>
<td>Anti</td>
</tr>
<tr>
<td>@realCharter DO NOT get the vaccine!!! That’s what’s killing people!</td>
<td>Anti</td>
</tr>
</tbody>
</table>

Table 5.7: Sample of original tweets for Topic 1: Consequences of vaccination/non-vaccination. Tweets classified as Pro-vaxer, Anti-vaxer and Neutral by perception classifier
<table>
<thead>
<tr>
<th>Tweets</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Ministry of Health South West State has officially launched the Oral Cholera Vaccination campaign in Hudur District</td>
<td>Neutral</td>
</tr>
<tr>
<td>2 female polio workers shot dead in Quetta Two female members of a polio vaccination team in Quetta were shot dead</td>
<td>Neutral</td>
</tr>
<tr>
<td>The Center Of Disease Control Says Ebola Vaccine Only Works On White People! #Topbuzz</td>
<td>Neutral</td>
</tr>
<tr>
<td>RT @TannersDad: 1 in 2 in fifteen years 80% of Boys - Extinction in 25 years. #Autism #SViY See Vaccine Injury Yet?</td>
<td>Neutral</td>
</tr>
<tr>
<td>February 9 story aired on KCTV5 News Kansas City. More information on Vaccine Court in the comments! Injury...</td>
<td>Neutral</td>
</tr>
<tr>
<td>RT @ChristineMilne: Don’t forget about @Barnaby_Joyce opposing world leading, life saving cervical cancer vaccine because it might lead to</td>
<td>Neutral</td>
</tr>
<tr>
<td>Infants were sick during immunisation etc. People will panic if they feel that vaccines have take the life of infants</td>
<td>Neutral</td>
</tr>
<tr>
<td>02/08/2018: MinnPost: Belief in conspiracy theories linked to anti-vaccine skepticism</td>
<td>Neutral</td>
</tr>
<tr>
<td>Scientists have developed a novel universal vaccine to combat influenza A viruses. The new vaccine aims to produce</td>
<td>Neutral</td>
</tr>
<tr>
<td>RT @PHarsanyi: @jakobschroeder @BrixAnja @tv2danmark (2014) Reduction in HPV prevalence—no evidence to support HPV vaccination reduces H</td>
<td>Neutral</td>
</tr>
<tr>
<td>RT @LaurenceVick: Throat cancer campaigners urge vaccinating boys against HPV Virus @TCF_Foundation</td>
<td>Pro</td>
</tr>
<tr>
<td>#Vaccination is a must. That’s 4,000 more mothers, brothers, wives and fathers dead each week. If you’re #sick, sta</td>
<td>Pro</td>
</tr>
</tbody>
</table>
Hello! Happy Sunday. Vaccines do not cause autism. Even if they did, an autistic child is better than a dead one. Thanks for reading.

The world’s only Russian vaccine effective against Ebola!
RT @BallouLab: Yep, not a single fungal vaccine out there. Hope the medmycol community can change this in the next ten years.

@JBDoes180 Hope she feels better soon. Make sure your family gets the flu vaccine. We all had it and it was awful.

RT @animalFndly: It’s National Cat Health Month and keeping your cat’s vaccines up-to-date can help them live a long and healthy life. More

Reminder! Getting your #flushot protects the vulnerable. Get yours at #LondonDrugs and a lifesaving vaccine will be

RT @timsandle: Scientists have developed a novel universal vaccine to combat influenza A viruses. The new vaccine aims to...

West Ham news: Cancer-stricken fan helped by footie supporters to fund her vaccine

RT @debunkdenialism: HPV vaccines are safe and effective. #vax

RT @stevescrutton: The campaign to make vaccination mandatory continues relentlessly in ‘the land of the free’. Free no more, if would see

Lead Developer Of HPV Vaccine Admits Its a Giant, Deadly Scam

RT @Lawfirm_MA: Those who don’t sicken quickly or drop dead in an obviously causal manner following vaccination may instead be struck with
| RT @r1dgyd1dge: @abcnews @GregHuntMP @TurnbullMalcolm Life threatening side affects with #gardasil vaccination. Do your research before yo | Anti |
| ‘Science is still out’ on #autism, vaccine link, new health official says - WWL : | Anti |
| RT @VaccineChoiceCA: Chicken pox vaccine linked with shingles at the vaccination sight in some children #LiveVirus #InformedConsent #NoMand | Anti |
| Here is your Tide Pod info - did you know it is in your childs #vaccine? Spread! | Anti |

Table 5.8: Sample of original tweets for Topic 2: Promotion of vaccination/non-vaccination. Tweets classified as Pro-vaxer, Anti-vaxer and Neutral by perception classifier

The tweet pool in Topic 1 for Pro-vaxer, Anti-vaxer and Neutral all incline towards the outcome of the vaccine. This is illustrated in the tweets ‘Flu Vaccine Increases Your Risk of Infecting Others by 6-Fold, Study Suggests’ and ‘So this woman didn’t die because she could afford the vaccine. Yes or no will suffice.’ which report the aftermath of vaccine consumption. For Topic 2, the tweets ‘RT @TannersDad: 1 in 2 in fifteen years 80% of Boys - Extinction in 25 years. #Autism #SViY See Vaccine Injury Yet?’ and ‘Lead Developer Of HPV Vaccine Admits Its a Giant, Deadly Scam’ suggest advertising strategies for the marketable environment. Even though there is an overlap among themes within a tweet, i.e. a tweet can be considered both as a ‘consequences of vaccination/non-vaccination’ and ‘promotion of vaccination/non-vaccination’, the final outcome is taken by the summation of probability scores of the words falling under each topic or category.
5.5 Analysis of Monthly Differences in Public Emotion and Sentiment

*Research Question 4: How does the public emotional response about vaccine change throughout the year?*

![Figure 5.11: Mean scores of emotions across each month](image)

From Figure 5.11, it can be seen that emotion ‘trust’ and ‘negative’ were consistent throughout the year thus illustrating that public trust towards vaccine development and negative views or criticism towards vaccine tends to be temporally invariant. Public acceptance for the vaccine will push the critics to rebut it creating an endless chain of acceptance and rejection. Almost all emotion scores were consistently uniform throughout the year.

In order to analyze the difference in emotions by month, a two-way MANOVA was conducted to test the hypothesis that there would be one or more mean differences between emotions with respect to public outlook and month.
The first step is to analyze the multivariate test results which provide the effects and significance of the independent factors. A statistically significant multivariate effect was obtained for month, Wilks Λ = 0.986, F (220, 17351986.75) = 124.45, p < 0.005, thus rejecting the possibility of the change in emotions occurring due to chance.

The effect size of the difference between emotions for each month was very small, partial $\eta^2 = 0.001$. Since the dataset consisted of approximately 1.9 million tweets, even the smallest, trivial differences between emotions became statistically significant. However, we failed to detect a clinically important difference as the tweets related to common discussion topics. Thus, we can conclude that even the significant difference is evident, there are no clinically significant month-by-month changes in emotion or sentiment over the course of the year.

5.6 Analysis of Difference in Sentiment and Emotion by Public Outlook towards Vaccination

Research Question 5: How do the emotions differ in people who support, reject or maintain a neutral view towards vaccination and how does that change throughout the year?

The above question can be answered by applying MANOVA to each emotion extracted from tweets using the NRC sentiment dictionary with respect to each of the three groups of Pro-vaxer, Anti-vaxer and Neutral. Figure 6.12 delineates emotions across Pro-vaxer, Anti-vaxer, and Neutral tweets.
Figure 5.12: Mean scores of emotions across each month w.r.t Pro-vaxer, Anti-vaxer and Neutral tweets
The multivariate test showed a statistically significant change in the differences in emotions between the three outlook by month (the month-by-outlook interaction), Wilk’s Λ = 0.989, F(110, 14202918.24) = 194.45, p < 0.01, partial η² = 0.001. However, this effect is very small and not clinically significant.

The main effect of public outlook toward vaccination was both statistically and clinically significant, Wilk’s Λ = 0.948, F (20, 3795886) = 5130.83, p < 0.01, partial η² = 0.026. The multivariate effect size for the effect of outlook towards vaccination implies that 2.6% of the variance in the emotions was accounted by public outlook towards vaccination. Thus, we can infer that the perceived emotions for a given tweet rely significantly on whether the tweet falls under the category of Pro-vaxer, Anti-vaxer or Neutral. While determining how the category of tweeter differ for the eight basic emotions, all emotions seems to have significant effect on Pro-vaxer, Anti-vaxer and Neutral. No anomaly was detected in the results that would deny effect of emotions on the outcome.

When each of the eight derived emotions is mapped across the graph for each month according to the three categories, variation between emotions can be perceived as the time changes. It can be seen that the emotions anticipation, joy, surprise and trust exhibit no difference among all the three types of public views towards vaccination. The adverse emotions such as anger, disgust, fear, sadness and negative score high on Anti-vaxer tweets than Neutral and Pro-vaxer tweets. It posits that tweets being classified as Anti-vaxer express more outwardly negative words to vocalize their opinions. The constant scores of emotions joy, trust and positive for both Pro-vaxer and Anti-vaxer are quite perplexing as one would anticipate acquiring more response for optimistic emotions from tweets being classified as Pro-vaxer. This cannot be solidified since many of the tweets are categorized as Neutral if they are incomplete in nature.

Given the statistical and practical significance of the multivariate test, the univariate tests for effects of public outlook and its interaction on each
emotion can be determined. The emotions anger \((F(2, 1897952) = 11175.51, p < 0.005, \text{partial } \eta^2 = 0.012)\), disgust \((F(2, 1897952) = 28605.98, p < 0.005, \text{partial } \eta^2 = 0.029)\), fear \((F(2, 1897952) = 22333.3, p < 0.005, \text{partial } \eta^2 = 0.023)\), sadness \((F(2, 1897952) = 31618.62, p < 0.005, \text{partial } \eta^2 = 0.032)\) and negative sentiment \((F(2, 1897952) = 26723.83, p < 0.005, \text{partial } \eta^2 = 0.027)\) differ significantly by public outlook towards vaccination.

After examining the effects of emotions on public outlook as a group, Tukey’s post-hoc tests on the significant emotions derived from univariate results were performed to isolate the emotions and see its independent effect on the public outlook. The result for Tukey’s post-hoc test is tabulated below which exhibits significant differences emotional responses.

<table>
<thead>
<tr>
<th>Emotion</th>
<th>n</th>
<th>Mean</th>
<th>SD</th>
<th>Pro-vaxer</th>
<th>Anti-vaxer</th>
<th>Neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pro-vaxer</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anger</td>
<td>911841</td>
<td>0.27</td>
<td>0.51</td>
<td>-0.15</td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>Disgust</td>
<td></td>
<td>0.33</td>
<td>0.56</td>
<td>-0.23</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td>Fear</td>
<td></td>
<td>0.58</td>
<td>0.75</td>
<td>-0.30</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td>Sadness</td>
<td></td>
<td>0.41</td>
<td>0.61</td>
<td>-0.33</td>
<td>0.10</td>
<td></td>
</tr>
<tr>
<td>Negative</td>
<td></td>
<td>0.87</td>
<td>0.91</td>
<td>-0.36</td>
<td>0.19</td>
<td></td>
</tr>
<tr>
<td>Anti-vaxer</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anger</td>
<td>189561</td>
<td>0.43</td>
<td>0.64</td>
<td>0.15</td>
<td>0.20</td>
<td></td>
</tr>
<tr>
<td>Disgust</td>
<td></td>
<td>0.56</td>
<td>0.69</td>
<td>0.23</td>
<td>0.35</td>
<td></td>
</tr>
<tr>
<td>Fear</td>
<td></td>
<td>0.89</td>
<td>0.90</td>
<td>0.30</td>
<td>0.43</td>
<td></td>
</tr>
<tr>
<td>Sadness</td>
<td></td>
<td>0.73</td>
<td>0.79</td>
<td>0.33</td>
<td>0.43</td>
<td></td>
</tr>
<tr>
<td>Negative</td>
<td></td>
<td>1.23</td>
<td>1.06</td>
<td>0.36</td>
<td>0.55</td>
<td></td>
</tr>
<tr>
<td>Neutral</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anger</td>
<td>796586</td>
<td>0.22</td>
<td>0.50</td>
<td>-0.05</td>
<td>-0.20</td>
<td></td>
</tr>
<tr>
<td>Disgust</td>
<td></td>
<td>0.23</td>
<td>0.49</td>
<td>-0.12</td>
<td>-0.35</td>
<td></td>
</tr>
<tr>
<td>Fear</td>
<td></td>
<td>0.46</td>
<td>0.71</td>
<td>-0.12</td>
<td>-0.43</td>
<td></td>
</tr>
<tr>
<td>Sadness</td>
<td></td>
<td>0.31</td>
<td>0.58</td>
<td>-0.10</td>
<td>-0.43</td>
<td></td>
</tr>
<tr>
<td>Negative</td>
<td></td>
<td>0.68</td>
<td>0.87</td>
<td>-0.19</td>
<td>-0.55</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.9: Tukey’s post-hoc results: all differences are significant at the 99% confidence level

It can be illustrated from the table above that emotion sadness is the score for sadness is 0.43 greater for the Anti-vaxer than Neutral category, and 0.3 greater than the Pro-vaxer category, postulating that people displaying refuting opinion towards vaccine tend to express more sadness than people supporting
vaccines and maintaining a neutral view towards the vaccine.

A visualization of how emotions tend to vary over time period given the public outlook is depicted below in Figures 5.13, 5.14, 5.15.

Figure 5.13: Mean scores of emotions for Pro-vaxer tweets throughout the year

Figure 5.14: Mean scores of emotions for Anti-vaxer tweets throughout the year

Taking a closer look at the emotions, it can be seen that ‘fear’ is one of the prominent emotions amongst tweeters. As discussed earlier, any claim rebutting vaccine efficiency, irrespective of having empirical support, creates a
significant impact on society. Public worry over these claims and fears on an imminent danger, even if they are not real, thus restricting their ability to see the whole picture. Their ability to think critically is limited and the words are spread creating a public health problem. Public confidence about vaccination erodes because of real or perceived risks associated with immunization, and thus, in turn, may lead to lower vaccination coverage and loss of herd immunity [47]. This can be improved by educating people with scientific claims as negative emotions are expected to have a positive relationship with information insufficiency [48].
6 Discussion

The framework designed for the study is successfully able to distinguish between the outlook possessed by tweeters for the vaccine by taking their expressions derived from the tweets as a preliminary data source. Around 77.5% of the harvested tweets were relevant or informative for the vaccination study. As observed in the sample dataset, tweets exhibiting dubious or no attitude or incomplete, which were tagged as ‘Neutral’, were dominant in the dataset and displayed the same properties when tested on evaluation data. This characteristic might be the outcome of the manual annotation of tweets rather than applying a automatic annotation model [57].

Even though adding either of the emotion scores, sentiment scores or topics did not affect the model categorizing between Pro-vaxer, Anti-vaxer and Neutral significantly, it still made a significant impact when none of them were administered in the model by incrementing the accuracy by almost 10%. Thus, we conclude that all of the emotion, sentiment, and topic features provide potentially useful information for classification of outlook towards vaccination [58].

Since the rules specified by the microblogging platform allow us to harvest only 10% of the posted tweets, an enormous collection of data is still left unexplored. Since some tweets cast ambiguity amongst annotators, it became difficult to agree on a tweet’s true category in many cases. The confusion matrix reveals that a large portion of Pro-vaxer and Anti-vaxer tweets are getting misclassified as Neutral. This can be justified by the differing opinions among raters. If fully trained cognitive human beings possessing thinking and judg-
ment capabilities can have different views for a certain scenario, it is impolitic to expect any better performance by a machine.

Nonetheless, it is imperative to note that the misclassification rate between Pro-vaxer and Anti-vaxer among themselves is very low. Thus, even with insufficient information, the model is able to distinguish an attitude completely opposite from its own. This can be endorsed by a higher AUC score. This might benefit related institutions and campaigns to develop targeted intervention ideas accordingly to increase the vaccination acceptance rate. The lower F1-measure resulted from the high rate of misclassification as Neutral tweets.

The naive Bayes classifier is considered as one of the simplest models as it assumes that the features of this model are independent of each other. Because of its independence assumption, the parameters of each feature are learned separately thus simplifying the learning process, especially with a large number of features [59]. Some studies utilize the naive Bayes model as a baseline model for evaluating the performance of custom-designed classifiers [60][61], while some attempt to build a better model over the naive Bayes [62]. However, in our study, it can be seen that while naïve Bayes is performing relatively well on the sample data, its performance is worse when applied to unseen data. The ensued performance might be the influence of skewed data acquired through tweets. Even though we applied stratified sampling on the dataset to reduce bias, as stated earlier, the dataset was dominantly inclined towards neutral and positive tweets over others. This might have led the naïve Bayes model to choose weights poorly for the decision boundary due to the under-studied bias effect that shrinks weights for classes with few training examples [63].

It can also be seen that for some models such as a k-nearest neighbor, neural network and naive Bayes, the unigram feature set performs better than unified-grams or bi-grams on the evaluation dataset. A movie review done by Pang et al. in 2002 showed that the presence of unigram features in the
model outperformed all the models employed with alternative features [64]. However, another study by Dave et al. in 2003 for product review revealed that bi-grams and tri-grams worked better for classification [65]. Higher order n-grams provide a better representation of text as it would be known which words combine with other words [66]. It is easier to detect the opinion of a person in a simple sentence by accounting for each word in the text. However, if the text contains words indicative of opposite sentiment such as sarcasm which appears constantly on social media, the model will fail to take this into account. While n-grams capture patterns of sentiment expressions better with increasing order, unigrams provide good coverage of data [67].

Studies have shown that adding parts-of-speech features contributes to a better performing model, where each word is identified as a noun, adjective or verb and counted at the end yielding features [68]. Other textual features include count of keywords, presence of hashtags and their count and number of followers and followees, URL links have shown to improve the performance of the classifier models [69]. Augmenting the feature space by introducing polarity features is a common technique [70]. Some studies also implement linguistic and rhetorical features to boost up the results [71]. In reference to future work, these features can be added and analyzed to potentially improve the models.

While harvesting tweets, 78 keywords were employed to garner data from Twitter. These keywords belonged to a large pool of words occurring not only for vaccination but in a broad spectrum of other contexts as well. Even though the tweets were retrieved based on terms closely related to vaccination, we anticipated the resulting themes to categorize upon a wide variety of topics such as types of diseases, types of vaccines, vaccine uptakes among people or even public perception towards vaccines given the diversity of the study. However, after employing LDA, the model was able to derive only 2 topics within the enormous corpus. To ensure if it is possible to derive more topics from the
corpus, perplexity scores were assessed until 200 topics. However, the score did not decrease at all rendering 2 topics as the best fit for the corpus.

In the above case, it can be said that even though the keywords for harvesting tweets were diverse in nature, the ultimate focus of the study was just ‘vaccine’, thus justifying a small number of topics. The topics derived from LDA were based on information presented in the tweets rather than the mathematical representation of the keywords. The two-topic solution implies that the public shows more interest in talking about the efficacy of vaccination and their promotions rather than specific facts and beliefs revolving around vaccination or presenting specific opinions regarding vaccination uptake. The claim that increase in public acceptance regarding vaccine increases with knowledge flow seems to be complying with our results, considering promotion of vaccines is one of the derived topics from the tweets.

The role of emotion in decisions regarding healthcare behavior has been a topic of interest [87]. Numerous studies are recorded in the past and are ongoing for analyzing the link between public emotions towards vaccine uptake and vaccination rates [88,89,90]. Public response is highly affected by current vaccine-related events. These events possess the potential to wane public confidence towards vaccination. Such is an incidence of the Disneyland measles outbreak in 2015 which illustrated the growing problem of vaccine refusal [73]. Prior studies reveal diverse motivations to refuse vaccine, including suspicions about vaccines causing autism, the presence of toxins such as mercury and aluminum, religious beliefs, distrust in government or healthcare services, distrust in pharmaceutical companies and preference towards natural lifestyle [74,75].

Even though the vaccine is the most important public health intervention towards prevention of infectious disease is mostly driven by religious and philosophical reasons. From Figure 5.12, it can be seen that ‘disgust’ is also one of the prime emotions elicited through tweets. Disgust may influence at-
titudes towards vaccines with two opposing hypotheses on the directionality of the association. As vaccines help the immune system by preventing infection, individuals with heightened disgust scores might hold more confidence towards vaccines to prevent themselves from diseases. In contrast, individuals with heightened disgust scores might be antipathetic as they perceive vaccines themselves as contaminants. Some studies also claim that people with high disgust scores hold a more negative attitude towards vaccines [81,82]. This is supported by our findings as to the mean negative emotion scores highest (1.23) for anti-vaxer tweets.

Public trust in the safety and efficacy of vaccines is one of the key factors for the success of immunization programs globally [85]. However, allegations of harm from vaccines have been so loud and widespread that they pose a threat to immunization programs and trust in health authorities and medical communities. Clinicians and public health leaders are been taken for granted because of the magnitude of the act of trust. The refusal rate for mandatory vaccines is also an indicator of weakening public trust in vaccines. Studies illustrate that it is imperative for personal doctors and medical authorities to educate parents about the importance of the vaccine and to reassure them about its safety [20,91]. Keeping transparency between government agendas for vaccine uptake and the public plays a vital role in the public’s vaccine decision making. Past experience with a vaccine is also treated as a strong predictor for declining vaccine intake. Delaying, refusing or regretting having a vaccine in the past influences a person’s attitude towards vaccination [85].

The presence of thimerosal has launched a new controversy for vaccine refusals and bans. Drivers of this controversy include incomplete science, political motivation, financial motivation and philosophical and religious objections to immunizations, or some constituents used in vaccine preparation [92]. These controversies have initiated fear among those in the public who have estab-
lished inaccurate views towards medical science. These fears are the result of irrational concern over vaccine safety, religious beliefs and misinformation or ignorance. As noted by Kendeou, when a person ends up in a state of negative emotion, they tend to focus more on negative information than others because of the narrowness of attention [93].

The fear among the public generated by false threats – like getting the flu from the influenza vaccine – restricts a person’s ability to see the whole situation. That metaphorical tunnel vision can limit people’s ability to think critically. A study by Powell suggests that fear could also change the minds of people who don’t support vaccines. They focused on spreading a message about the severity and risk of contracting MMR convincing parents that vaccines are necessary [94]. Powell’s study concluded that even if people thought that there was a little bit of risk to a vaccine, if persuaded by medical practitioners that there are a lot of risks for not vaccinating, it might overall tip the scale in favor of vaccination [86]. The public should be motivated to study the benefits and risks of vaccination and balance them to overcome these fears.

For people strictly classified as Pro-vaxer or Anti-vaxer, their decision to get vaccinated or not is likely to be straightforward based on their perception. However, people who are hesitant towards vaccination are those who have no knowledge of vaccines, likely to be misinformed about the vaccine, no time or interest for vaccination or bearing little or no confidence in vaccines as they are unsure of their assessment of vaccines. Studies claim that the effects of most interventions, except mandatory vaccination, are relatively low and suggest that the link between vaccine attitudes, beliefs, knowledge, and behavior is multifaceted. In fact, some studies show that strategies aimed at correcting vaccination misinformation among vaccine skeptics have no effect, or even backfire [83], while employing mandatory vaccinations has led to employers facing litigation [84].
Since most of the disease preventable vaccinations such as MMR, HPV, DTaP, Hepatitis A and Hepatitis B. are given during adolescence, consent from parents is required for the procession. Thus, parental acceptance towards vaccination plays a crucial role in augmenting vaccine uptake to eradicate the prevalence and incidence of vaccine-preventable diseases. Studies reveal that providing adequate information through a sharable medium improves parents’ knowledge regarding vaccination [76]. Confidence in the safety of vaccines and knowledge of its potential adverse effects increases the intention of vaccination [72]. Furthermore, some studies claim that demographics play a role in vaccine uptake [77].

Knowledge, attitudes, parental beliefs and education levels can independently influence parents’ intention to vaccinate [78]. Some studies suggest that trust in doctors and government along with past experience with vaccination are associated with vaccine acceptance rate [79]. People develop a trust bond with their family doctors who can help educate their patients regarding vaccines since parental acceptance towards vaccination is directly proportional towards vaccine acceptance [49][50]. Studies claim that a practitioner’s ability to provide effective professional advice about vaccines could be undermined if directly promoted to parents [51]. Furthermore, practitioners should be able to provide effective professional advice about vaccines to promote vaccination [80].
7 Conclusion

Public opinion plays a crucial role in any domain, especially in health care as reviews stated by the public help us gain insight on the problems faced by our healthcare system and can be utilized to design a strategy to tackle these problems. Health care professionals use social media for sharing information about health and healthcare policies to promote healthy behavior.

We implemented this study by harvesting tweets and classifying them as relevant to vaccination or not in the first stage. The neural network model comprising of both uni-grams and bi-grams was tagged as the best performing classifier based on accuracy and computational time which successfully classified 90.84% of the tweets. Health services monitoring Twitter behavior for vaccines can analyze a surge in tweets occurring due to vaccine-related disease outbreaks or research developments.

The relevant tweets were then further classified as people supporting vaccines (Pro-vaxer), people opposing vaccines (Anti-vaxer) and maintaining a neutral stance (Neutral). The same classifier was employed by adding emotions and sentiments derived using EmoLex and topics derived from LDA as features. The classifier resulted in 66.77% of correctly classifying the tweets as per public outlook. Understanding the content and implications of conversations that form around the tweets derived as per public outlook on social media can aid health organizations and practitioners in creating a meaningful exchange of ideas that can lead to a significant impact on vaccine uptake.

While performing topic modeling on the relevant tweets, the results sup-
ported a 2-topic solution which implicated that public interest emphasizes more on the effects or consequences of vaccine and their marketing strategies than delving into vaccine types, intake or general opinion.

The study demonstrated that even though there was significant difference between emotions and sentiments throughout the year, no clinically significant difference was noted, thus suggesting discussions about vaccination on Twitter stays relatively constant throughout the year. The results concluded in both statistically and clinically significant difference between emotions and sentiments between public outlook, thus inferring that change in public emotions can play as an adaptive role to take necessary actions for increasing vaccine acceptance rate.

The expression of anger, disgust, fear, sadness, and negative sentiment all had significantly higher scores in Anti-vaxer tweets than Pro-vaxer or Neutral tweets. Implementing target intervention programs and knowledge-centered campaigns by medical care addressing these negative emotions can help foster vaccination acceptance.
8 References


of Reviews. Health promotion and chronic disease prevention in Canada: research, policy and practice, 36(4), 63.


[41] Laura A.V. Marlow, Jo Waller Jane Wardle (2007) Trust and Experience as Predictors of HPV Vaccine Acceptance, Human Vaccines, 3:5, 171-175, DOI: 10.4161/hv.3.5.4310


[43] Peretti-Watel, P., Raude, J., Sagaon-Teyssier, L., Constant, A., Verger, P.,
Beck, F. (2014). Attitudes toward vaccination and the H1N1 vaccine: Poor people’s unfounded fears or legitimate concerns of the elite? Social Science Medicine, 109, 10-18.


[81] Clay R (2016) The behavioral immune system and attitudes about Vaccines: Contamination aversion predicts more negative vaccine attitudes. Social
Psychological and Personality Science, 8, 162.


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9 List of Keywords

vaccine, vaccination, immunize, immunization, immunise, immunisation, antivaccine, antivaccination, antivax, antivaxx, antivaxxer, antivaxer, vaxxed, saynotovaccine, autism + vaccine, autism + vaccination, autism + immunize, autism + immunization, autism + immunise, autism + immunisation, saynotovaccine, autism + vaccine, autism + vaccination, autism + immunize, autism + immunization, autism + immunise, autism + immunisation, exvaxxer, stopmandatoryvaccine, vaccinedangers, vaccineskill, vaccineinjury, educatebeforeyouvaccinate, vaccinesharmactually, vaccineinjuryawareness, antivak, antivaksin, antivac, vaccineingredients, vaccinescauseautism, vaccinescausedisease, vaccinecorruption, vaccinesaveslives, justvaccinate, vaccinesmaimandkill, vaccinescampaign, goodluckwithyourvaccines, vaccinesrevealed, vaccinedamage, vaccinetruth, antiflushot, flushot, pro-vaccine, fluseason, vaccineevolution, HPV, measles, MMR, TDAP, anthrax vaccine, Hepatitis A, Hepatitis B, tetanus, rabies, smallpox + vaccine, chickenpox + vaccine, Meningitis, pro-safe, thimerosal, cdc + vaccine, who + vaccine, Donald Trump + vaccine, Australian Vaccination skeptics Network, Christian Science, GreenMedInfo, Infowars + vaccine, NaturalNews + vaccine, flu + vaccine, flu + vaccination, influenza + vaccine, influenza + vaccination, anti + flu + shot