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Sentiment analysis in infodemic management: leveraging the eppm Risk communication model

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Abstract

Infodemics are the rapid spread of false or misleading information related to public health emergencies, often through digital platforms. They can cause confusion, fear, and even harm to public health. This study investigates the application of sentiment analysis for infodemic management during disease outbreaks. Leveraging the Extended Parallel Process Model (EPPM) of risk communication, the research aims to categorize rumors based on their perceived threat level (high, medium, or low). Machine learning is employed to analyze infodemic text data collected from two Nigerian states (Oyo and Bauchi) to assess threat appraisal according to the EPPM model. The findings can inform targeted interventions for effective infodemic management before, during, and after outbreak of diseases.

Keywords: Infodemics, Sentiment analysis, Extended Parallel Process Model

1. Introduction

Nigeria, with its diverse population and extensive media landscape, has been grappling with the detrimental effects of infodemics. The rapid dissemination of misinformation, particularly via social media, has exacerbated public health crises such as Ebola, Lassa fever, and COVID-19. Despite efforts by the Nigerian Center for Disease Control (NCDC) and other health agencies, traditional reactive approaches have proven insufficient and inefficient in controlling or reducing these challenges (Shobowale, 2021).

Risk communication is crucial for effective public health responses to crises. The Extended Parallel Process Model (EPPM) provides a theoretical framework for understanding how individuals perceive, understand and respond to risk messages and comments. However, the potential of sentiment analysis to enhance risk communication within this model in the Nigerian context remains largely unexplored (Abbas et. al., 2022).

This study aims to investigate how sentiment analysis, applied within the framework of the EPPM, can enhance risk communication strategies in Nigeria to combat infodemics and build community resilience. By analyzing data collected from NCDC to understand public sentiment towards health crises, researchers can develop targeted messaging and interventions to mitigate the spread of misinformation and foster trust in expert guidance.

2. Literature Review

An infodemic is an overabundance of inaccurate information hindering informed decision-making during crises. It can exacerbate economic, health, and social challenges. Risk perception, influenced by culture, experience, and media, shapes individual responses to threats. Infodemics distort risk perception, leading to underestimation or overestimation of risks, fueling fear and misinformation, as exemplified in this relationship by COVID-19 pandemic (Suleiman, 2022).

Misinformation about the virus' severity led to decreased mask usage and other preventive measures. Accurate information from reliable sources is crucial for mitigating these negative impacts (Anwar, 2020). Research supports the link between infodemics and distorted risk perception. For example, misinformation about COVID-19 reduced adherence to preventive measures due to lowered perceived susceptibility. Social media amplified the crisis by disseminating false information, contributing to increased fatalities. Conversely, exposure to accurate information from World Health Organization (WHO) increased risk perception and preventive behaviors (Bursztyn,2021).

Nigeria has faced significant challenges related to infodemics, especially during the COVID-19 pandemic. Social media is a primary conduit for misinformation. Studies highlight the impact of infodemics on public health outcomes, with misinformation influencing vaccination attitudes and non-compliance with health measures. A study by (Balakrishnan et al., 2022) and (Beebeejaun,, 2021) brought to light that the most common means by which misinformation spreads the most is through social media, and it’s usually at a high speed and is very difficult to manage its spread. Another growing research area is the impact of the infodemic on public health outcomes which was a study done by (Luo et al., 2021) where he indicated that most of the COVID-19 misinformation was associated with the wrong attitude towards vaccination and non-compliance with public health measures.

The efforts made so far in Nigeria in managing the infodemic have been strategies such as checking facts, community engagement, and public awareness and education. A study by (Sharma et al., 2021) pointed out the importance of community engagement in mitigating COVID-19 misinformation, which requires involving community leaders and influencers in sending out the right information. Another study (Isere & Ajayi, 2021) emphasized the need for journalists to be trained in executing fact-checking strategies to mitigate against infodemic, this is because the role of the traditional media cannot be pushed aside in reducing misinformation during disease outbreaks. (Williams et al., 2021) pointed out that there is a need to have ethical guidance when health information is being disseminated during public health emergencies and the need to also balance between having to spread accurate information and issues with protecting people’s personal information and privacy. Efforts to manage infodemics in Nigeria include fact-checking, community engagement, and public awareness. Community involvement and media training are emphasized as crucial strategies. Balancing accurate information dissemination with privacy concerns is also highlighted. Community resilience is the ability to recover from disease outbreaks with minimal damage. It involves accurate information, preparedness, and effective communication. The COVID-19 pandemic underscored the importance of community resilience, demonstrating the impact of misinformation on public health (Suarez & Alvarez, 2021).

Social cohesion, preparedness, and effective communication are key components of community resilience. Studies show that communities with high social cohesion are better equipped to handle disease outbreaks. Nigeria's response to the Ebola outbreak highlights the importance of community engagement, data analysis, and contact tracing in building resilience. Understanding risk behaviors is crucial for effective response. Factors influencing these behaviors include knowledge, trust in health authorities, and perceived efficacy of interventions (González-López et al., 2022).

The EPPM explains how individuals perceive and respond to threats. It focuses on threat appraisal and efficacy beliefs. Communities and individuals' perceived threat levels influence their motivation to follow public health guidelines. Combining machine learning and the EPPM model can enhance community resilience to infodemics. Machine learning can analyze data to identify patterns, predict risks, and inform targeted interventions. The EPPM provides a framework for understanding how individuals respond to threats. By integrating machine learning with the EPPM, tailored communication strategies can be developed to address specific community needs and vulnerabilities. Machine learning can also evaluate the effectiveness of interventions and refine strategies accordingly. Various machine learning techniques can be applied to different components of the EPPM, including supervised classification for threat appraisal, personalized recommendation systems for efficacy appraisal, and sentiment analysis for evaluating response effectiveness (Jahangiry et al., 2020; Popova, 2020).

From the research made by (Balakrishnan,2022), he observed that most Artificial Intelligence (AI) strategies used on fake news are basically for detecting or debunking fake news and only one targeted intervention, this project is not focused on detecting fake news but on risk perception and social behavioral change that affects community response to disease outbreaks and health solutions provided by the experts.

3. Methodology

The dataset that would be used for this study was collected between April 2023 to February 2024 by the NCDC communication team. The dataset consists of infodemic dataset for Oyo and Bauchi state. Oyo is the south-western part of Nigeria while Bauchi state is in the Northern part of Nigeria. Python programming language was used to clean the raw dataset as part of the process of preparing the data for analysis. The raw dataset as provided by NCDC does not consist of all necessary information to effectively provide efficacy appraisal analysis, based on the EPPM risk communication model, the data collected need to have both threat appraisal records and efficacy appraisal records. This was not the case probably because the data was collected to debunk rumor and not to study the underlying cause of the rumor which is human behavior that the EPPM risk communication model addresses. Thus, due to this, this study focuses on the threat appraisal component of the EPPM risk communication model. The python drop () method was used to remove columns that were not relevant to the study. After the drop () method was applied the table column size reduced, then the data. isnull() function was applied again to check for missing value, thus no missing value was found.

The data set was further checked for duplicate records using the python programming language command “data. duplicated”. The cleaned dataset consists of rumor column with corresponding different level of perceived threat ranging from low to high, using the EPPM risk communication model, perceived threat is high when rumor is perceived to cause harm or danger to an individual or the community while a perceived threat is low when a rumor does not pose any form of risk to an individual or a community. To properly work with the rumor column there is need to convert the rumor text data to a numerical feature that the machine learning algorithm can understand, this is called feature extraction.

This study used the Count Vectorizer like the TF-IDF vectorizer to vectorize the rumor text data. Since the rumor text data is the independent variable while the risk rating is the dependent variable, more emphasis is made on the rumor text data to ensure that the text is devoid of any form of inconsistencies, this was achieved by applying python codes that removes stop-words, non-letter characters, converting all rumor text data to lowercase, filtering out common English stop-words and lemmatizing the remaining words, lemmatizing is bringing back words to its simple base form, for example "studying" would return "study" when lemmatized.

Fine-grained sentiment analysis was employed to assess the polarity of perceptions within the infodemic dataset. This process categorized infodemic data into high, medium, and low risk levels based on the EPPM model. By analyzing the emotional tone of digital text (positive, negative, or neutral), the study determined the level of concern or threat expressed within the data. For instance, similar to classifying product reviews as positive or negative, this analysis evaluated the sentiment of public reactions to health-related information.

4. Result and Discussion

Three supervised learning algorithms for sentiment analysis were used on the secondary dataset provided, this is to know which algorithm is the best to use based on the chosen type of sentiment analysis selected. This study used the Support Vector Machine (SVM) model on the dataset converting the Rumor column of the dataset to numerical vectors using COUNTVECTORIZER python library under the Scikit-learn (Sklearn), this is a rich library for machine learning in python. The model was evaluated using the f1 score, precision, recall and confusion matrix metrics to measure the performance of the model. From the result below as copied from the Jupiter notebook platform. The f1 score is approximately 52%, precision is 52% and recall is also 52%. The statistics below was generated from a python script.

Metric Statistics for SVM trained model

'f1_score': 0.5161290322580645, 'confusion_matrix': array ([[10, 8, 20], [4, 33, 11], [15, 17, 37]], dtype=int64), 'precision': 0.5161290322580645, 'recall': 0.5161290322580645}

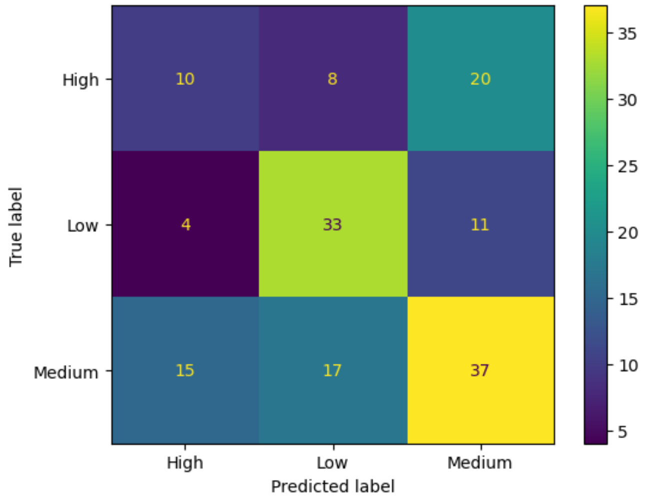

Figure 1: SVM Confusion Matrix Result Analysis

Accuracy is the total number classified correctly out of the test set, which are on the diagonal as indicated by the values 37, 33, and 10, respectively. These are usually called the True Positive (TP) or True Negative (TN), but based on the supervised label this study is using, TP is True High (TH), True Negative is True Low (TL), and True Neutral is True Medium (TM). To find the accuracy mathematically as automatically generated by the Python script shown above, we use the accuracy formula below:

TH+TL+TM/TH+TL+TM+(All False High, Low and Medium of each classes) =10+33+37/10+33+37+4+15+17+8+20+11=80/155=0.5161290322580645x100=52% approximately.

The Naïve Bayes algorithm was applied on the dataset to see if there could be an improvement that can be better than the performance of the SVM algorithm that was first used, performance metrics was applied, and the result can be found below as automatically generated by a python script:

Metric Statistics for NAIVE BAYES trained model

{'f1_score':0.567741935483871,'confusion_matrix':array([[4,12,20],[2,27,19],[1,13,57]],dtype=int64),'precision': 0.567741935483871,'recall':0.567741935483871}

From the statistics, an improvement of about 4% was achieved, which shows that Naïve Bayes would be a better algorithm to use on the given secondary dataset compared to SVM algorithm that generated metrics of 52% accuracy.

NAÏVE BAYES Confusion Matrix Result Analysis

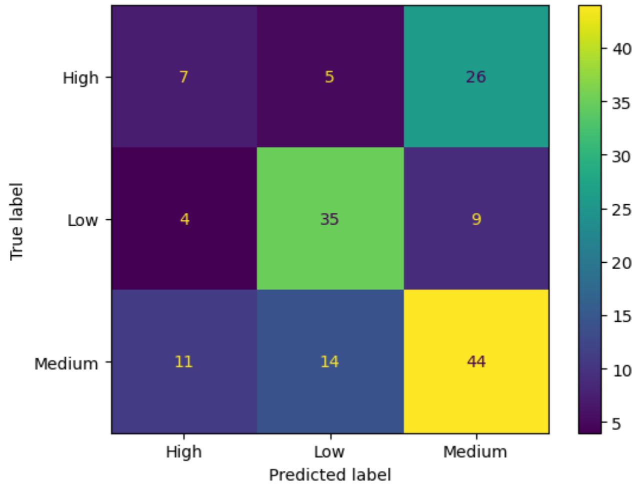

Figure 2: NAÏVE BAYES Confusion Matrix

Accuracy

The accuracy of the NAÏVE BAYES classification model can be manually calculated using the confusing matrix data, note that the True High (TH) = 7, the True Low =35 and the True Medium =44 using this information, the NAÏVE BAYES accuracy based on the confusion matrix can be calculated using the formula below:

TH+TL+TM/TH+TL+TM+(All False High (FH), False Low (FL) and False Medium (FM) ofeach actual labels) =7+35+44/7+35+44+4+14+11+5+26+9= 86/155 = 0.5548387096774194x 100 = 56%

Finding the correlations between two data components is possible with the use of a data analysis method called logistic regression. There is typically a limited set of possible outcomes for the prediction, such as yes or no. Lawton, G. (2022). Logistic regression is basically supervised learning that is good for classification.

To predict a categorical variable as opposed to a continuous one, logistic regression assesses the relationship between a dependent variable and one or more independent variables.

Metric Statistics for LOGISTIC REGRESSION trained model

{'f1_score': 0.6, 'confusion_ matrix': array ([[2, 9, 19], [2, 39, 21], [1, 10, 52]], dtype=int64), 'precision': 0.6, 'recall': 0.6}

LOGISTIC REGRESSION Confusion Matrix Result Analysis

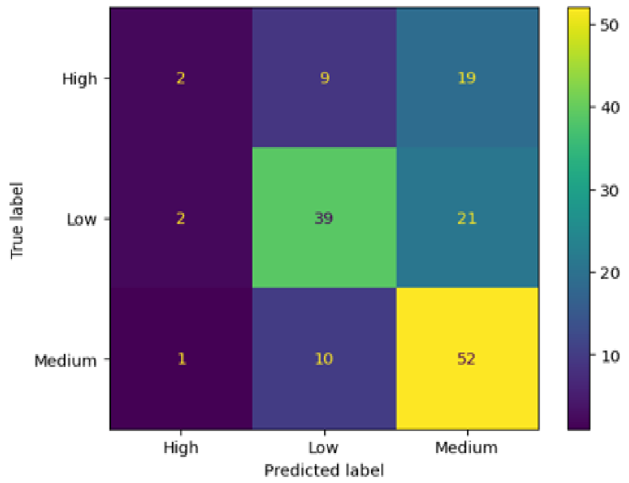

Figure 3: Logistic Regression Confusion matrix

Accuracy

The accuracy of the logistic regression classification model can be manually calculated using the confusing matrix data; note that the true high (TH) = 2, the true low = 39, and the true medium = 52. Using this information, the logistic regression accuracy based on the confusion matrix can be calculated using the formula below:

TH+TL+TM/TH+TL+TM+(All False High (FH), False Low (FL) and False Medium (FM)ofeach actual labels) =2+39+52/2+39+52+2+1+10+9+19+21= 93/155 = 0.6 x 100 = 60%

In conclusion, based on the confusion matrix and other metrics such as accuracy, precision, fi score, and recall applied to the different models tested, the logistic regression model emerges as the model with the highest percentage accuracy of 60% compared to other models such as Naïve Bayes and SVM with accuracy of 56% and 52%, respectively. This study finally chooses the logistic regression as the main model to use for this study. Exploratory Data Analysis (EDA) is a method that is usually applied to datasets that enables professionals to analyze datasets and further probe datasets for decision-making. EDA usually uses visualization for easy identification and explanation of the dataset. This project used a set of libraries in Python Django to explore the rumor dataset after creating the logistic regression model on Jupiter Notebook. The exploratory data analysis done in this study can be summarized below using the following data flow diagram in figure.

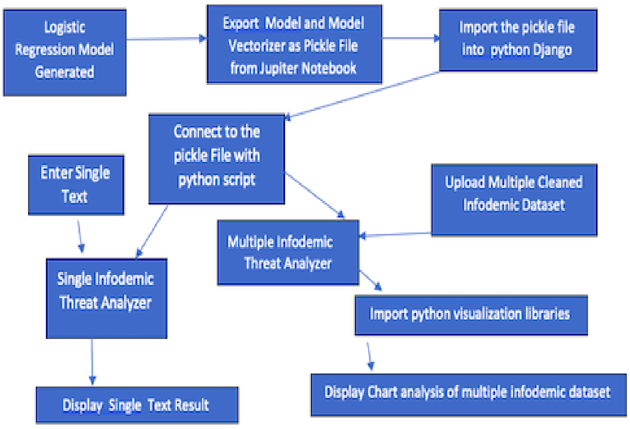

Figure 4: EDA Flow diagram describing the process

From the diagram above the data flow shows the process involved in exporting the logistic regression model generated in Jupiter notebook to Django. The exploratory data analysis tool used for this study is Django. Django is a free open-source web framework that is used for building web applications using python. The generated model and vectorizer are exported as a pickled file, a common format for serializing Python objects. This allows for storage and later retrieval without data corruption. Unlike human-readable formats like JSON or XML, pickled files are typically byte arrays. In Django, a script connects to the pickled file, accessing both the model and vectorizer. The vectorizer converts text inputs into numerical representations, enabling the model to process and analyze them. For the charts to be generated, python visualization libraries were imported these are the matplotlib libraries which are used to generate charts in Django.

In conclusion, the infodemic threat analyzer application developed works in two ways we have the single infodemic threat analyzer and the multiple infodemic threat analyzer. The single infodemic threat analyzer just needs an infodemic phrase, sentence or words and the model would automatically categorize the phrase or sentence as high threat, low threat or medium threat. While the multiple threat analyzer uses a bar chart to describe the number of infodemics received per state and shows which of the three categories is the highest. If a state has high number of threats appraisal, then the government needs to deploy tools and staff to investigate the source of infodemic and mitigate against it while if the threat appraisal is low then little or no action is needed by the government for a particular state.

Below are the screenshots and explanation of the graphical user interface of the web application:

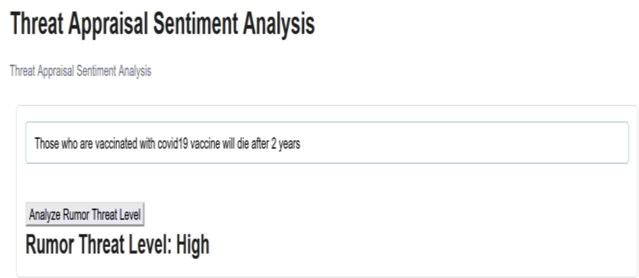

Figure 5: Single Infodemic Threat Analyzer with Sample Results

From the diagram above, a single phrase or text is placed in the text box and the sentiment analysis model automatically saved in the pickle file automatically and generate the rumor threat level category.

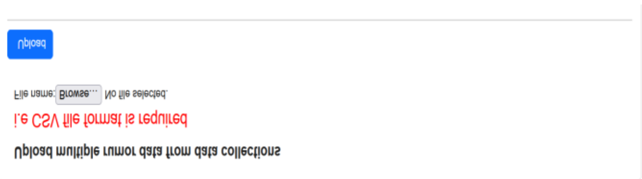

Figure 6: Upload multiple rumor data to the database from data collections.

From the figure above data is uploaded to the database from all data collection, thus data collected from each state are collated together and analyzed by state automatically using the sentiment analysis model.

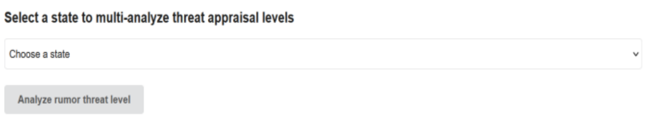

Figure 6: Interface for selecting which state to automatically analyze using the sentiment model.

This interface is for selecting a state by using the drop-down menu, based on the number of rumors that are categorized by the sentiment model, each rumor is analyzed to have High, Low and Medium label, the number of categories that's the highest describes the level of risk the state is currently whether high threat, low threat or Medium. Based on the EPPM model only the High threat and low threat are considered.

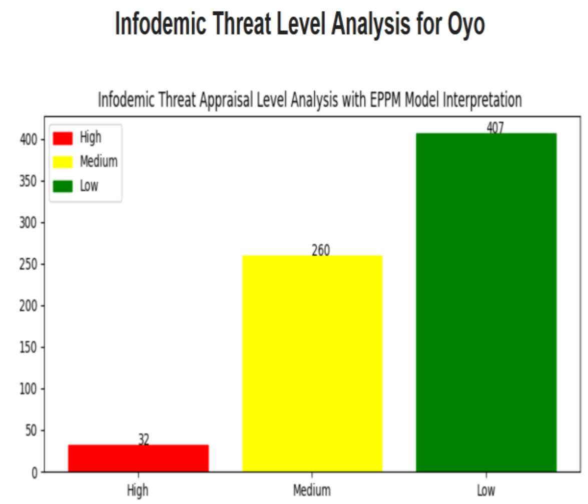

Figure 7: Oyo state threat appraisal analysis categorized using the logistic regression model.

Using the EEPM risk communication model, it states that when the infodemic threat appraisal is high the infodemic would be harmful to a community and when the infodemic threat level is low then the infodemic threat would not be harmful to a community.

From the bar chart above the state of Oyo has a good number of infodemics or rumors that are categorized as low threat which sums up to a total number of 407, the dormant or general rumor which are neutral or medium has a total sum of 260, the High infodemic threat is 32 making a total of 699 infodemics generated by the data collection done in the Oyo state communities. The high infodemic threat appraisal is about 5% while the low infodemic threat appraisal is about 58% and the neutral or the medium infodemic threat is 37%.

From this bar chart the government of Oyo state can work on the 5% high threat infodemics which pose a communication risk to the communities of the state, these infodemics can spread over time if not handled properly through community engagement and sensitization.

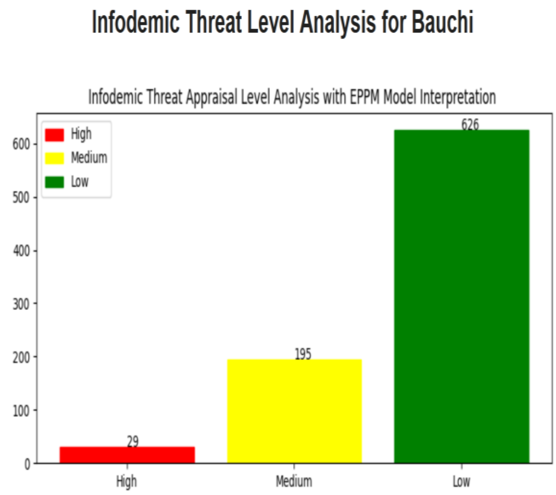

Figure 8: Bauchi state threat appraisal analysis categorized using the logistic regression model.

Applying the EPPM risk communication model to the description of the chart above, it shows that Bauchi State has infodemic threat appraisal that is about 3.0% High and 74% low. This means that the majority of the infodemics generated by the communities in Bauchi state have low threat appraisal.

Negligible infodemics which are categorized as Medium are at 23%, the total number of all infodemics generated by Bauchi state stands at 850 while the High threat appraisal is 29, the low threat appraisal is 626 and the negligible threat appraisal is a total of 195 respectively. The 3% high threat appraisal should be resolved by the government of Bauchi state through sensitization and community engagement to ensure the communities are getting the right information at the right time to avoid further spread of the infodemic.

5. Conclusion

Applying machine learning to risk communication models especially in public health areas can help public health expert reduce community resistance to expert solutions, this resistance comes because of unverified infodemics consumed by various communities through their belief system or influence from a community leader. When the infodemic datasets are properly collected and collated such that each label of the infodemics datasets does not contain noisy data, infodemic trends of a particular community can be monitored and the trained and test dataset can easily know what kind of infodemics is peculiar to a particular community and decision makers would be able to know what kind of interventions that appropriately fits such community.

This study advocates that debunking rumor or infodemics is not enough but going to the source of the rumor or infodemics at an earlier stage is the best approach to mitigating against it and as human behavior frequently changes infodemic data gathering should be a continuous exercise within communities.

Future work

This study only had access to threat appraisal data from the secondary dataset provided by the Nigeria CDC Communication department, there were no data found for efficacy appraisal to have a complete interpretation of the dataset using the EPPM risk communication model. For future work the secondary dataset should include efficacy appraisal data that gives respondent a choice of what they would do if there were experts solutions to a disease outbreaks that led to different sources of infodemics generated, for example if there is an infodemic that states that "People that takes COVID-19 vaccines would die after two years" there should be a follow up questions or an efficacy appraisal for example that indicates to the respondent that "on a scale of 1 to 5 would you take the COVID-19 vaccine?" respondent response to this questions would determine if majority of such communities would take the vaccine or due to the infodemic earlier stated would resist expert solutions.

Combination of the threat and the efficacy appraisal as described below are needed to properly define the EPPM communication model:

- High Threat and high efficacy level (Display Danger Control): Here danger is under control and people are willing to cooperate with experts (A call to action is required to ensure people are provided accurate information and solutions to the outbreak)
- High threat and low efficacy level (Display Fear Control): Here the rumor or misinformation needs to be investigated and education needs to be provided to reduce the fear of using public health expert solutions.
- Low Threat and high efficacy (lesser amount of danger control): People need to be educated about the risk of the outbreak.
- Low threat and low efficacy (People don't feel at risk): Educate about risk and solutions.

Future research can explore the combination of the threat and efficacy appraisal dataset and the use of other machine learning algorithms rather than the logistic regression model used in this study.

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