“Short is the Road that Leads from Fear to Hate”:
Fear Speech in Indian WhatsApp Groups

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ABSTRACT
WhatsApp is the most popular messaging app in the world. Due to its popularity, WhatsApp has become a powerful and cheap tool for political campaigning being widely used during the 2019 Indian general election, where it was used to connect to the voters on a large scale. Along with the campaigning, there have been reports that WhatsApp has also become a breeding ground for harmful speech against various protected groups and religious minorities. Many such messages attempt to instil fear among the population about a specific (minority) community. According to research on inter-group conflict, such ‘fear speech’ messages could have a lasting impact and might lead to real offline violence. In this paper, we perform the first large scale study on fear speech across thousands of public WhatsApp groups discussing politics in India. We curate a new dataset and try to characterize fear speech from this dataset. We observe that users writing fear speech messages use various events and symbols to create the illusion of fear among the reader about a target community. We build models to classify fear speech and observe that current state-of-the-art NLP models do not perform well at this task. Fear speech messages tend to spread faster and could potentially go undetected by classifiers built to detect traditional toxic speech due to their low toxic nature. Finally, using a novel methodology to target users with Facebook ads, we conduct a survey among the users of these WhatsApp groups to understand the types of users who consume and share fear speech. We believe that this work opens up new research questions that are very different from tackling hate speech which the research community has been traditionally involved in. We have made our code and dataset public\(^1\) for other researchers.

KEYWORDS
fear speech, hate speech, Islamophobia, classification, survey, WhatsApp

1 INTRODUCTION
The past decade has witnessed a sharp rise in cases of violence toward various religious groups across the world. According to a 2018 Pew Research report\(^2\), most cases of violence are reported against Christians, Jews and Muslims. The shooting at Christchurch, Pittsburgh synagogue incident and the Rohingya genocide are a few prominent cases of religion-centric violence across the globe. In most of these cases of violence, the victims were religious minorities and social media played a role in radicalizing the perpetrators. According to a recent report by the US commission mandated to monitor religious freedom globally, India is one of the 14 countries where religious minorities are constantly under attack. In India, most of the religious conflicts are between Hindus and Muslims\(^3\) who form 79% and 13% of the overall population, respectively. Recently, differences in opinions about the Citizenship Amendment Bill (CAB) have led to severe conflicts between the two communities in various parts of India.\(^4\)

There is not one clear answer to why such tensions have increased in the recent past, though many reports indicate the role of social media in facilitating them. Social media platforms like Facebook and WhatsApp provide a cheap tool to enable the quick spread of such content online. For instance, reports have shown that some recent cases of religious violence in India were motivated by online rumours of cattle smuggling or beef consumption\(^5\) on social media platforms. Similarly, messages inciting violence against certain groups spread across WhatsApp during the Delhi riots in 2020\(^6\).

However, due to the strict laws punishing hate speech in India\(^7\), many users refrain from a direct call for violence on social media, and instead prefer a subtle ways of inciting the readers against a particular community. According to Buyse\(^8\), this kind of speech is categorized as ‘fear speech’, which is defined as “an expression aimed at instilling (existential) fear of a target (ethnic or religious) group”. In these types of messages, fear may be generated in various forms. These forms include but are not limited to

\begin{itemize}
\item Harmful things done by the target groups in the past or present (and the possibility of that happening again).
\item A particular tradition of the group which is portrayed in a harmful manner.
\end{itemize}

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\(^1\)https://www.business-standard.com/article/pti-stories/usirf-recommends-india-13-others-for-countries-of-particular-concern-tag-india-rejects-report-120042801712_1.html

\(^2\)https://www.pewresearch.org/fact-tank/2018/06/21/key-findings-on-the-global-rise-in-religious-restrictions/

\(^3\)https://en.wikipedia.org/wiki/Hate_speech_laws_in_India

\(^4\)Cow's are considered sacred by Hindus in India and beef trade has always been a contentious issue between Hindus and Muslims\(^6\).

\(^5\)https://www.bbc.com/news/world/asia-india-50670393

\(^6\)https://www.pbs.org/newshour/real-life/whateria-genocide-india-2019-

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Table 1: Examples of fear speech (FS), hate speech (HS), and non fear speech (NFS). We show how the fear speech used elements from history, and contains misinformation to vilify Muslims. At the end, they ask the readers, to take action by sharing the post.

| Text (translated from Hindi) | Label |
|-------------------------------|-------|
| Leave chatting and read this post or else all your life will be left in chatting. In 1378, a part was separated from India, became an Islamic nation - named Iran . . . and now Uttar Pradesh, Assam and Kerala are on the verge of becoming an Islamic state . . . People who do love jihad — is a Muslim. Those who think of ruining the country — Every single one of them is a Muslim !!! Everyone who does not share this message forward should be a Muslim. If you want to give muslims a good answer, please share!! We will finally know how many Hindus are united today !! | FS |
| That’s why I hate Islam! See how these mullahs are celebrating. Seditious traitors!! | HS |
| A child’s message to the countrymen is that Modi ji has fooled the country in 2014, distracted the country from the issues of inflationary job development to Hindu-Muslim and patriotic issues. | NFS |

- Speculation showing the target group will take over and dominate in the future.

In this paper, we identify and characterize the prevalence of fear speech from messages shared on thousands of public WhatsApp groups discussing politics in India.

**Difference to hate speech**: At a first glance, fear speech might appear similar to the well known problem of hate speech. Table 1 provides an example comparing fear speech with hate speech. First we show a typical example of fear speech against Muslims. We can see the use of various historical information and related misinformation in the text. These portray the Muslim community as a threat, thus creating a sense of fear in the minds of the reader. One interesting thing to notice, is that there are no toxic statements in this post as well as in most other fear speech posts in general. This is different from hate speech, which usually contains derogatory keywords [20].

In order to further highlight the difference, we use an India specific hate lexicon [14] and a state-of-the-art hate speech detection model [3] and evaluate the fear speech dataset that we have developed in this paper (Section 3). Both of them perform poorly, scoring 0.53 and 0.49 as macro F1 scores respectively. This can be partially attributed to the toxicity in these hate speech datasets and the lexicon/models trying to mostly bank their predictions on that. Finally, empirical analysis using a toxicity classifier from the Perspective API [1], shows that the toxicity score of hate speech texts (0.57) is significantly ($p$-value < 0.001) higher than for our text containing fear speech (0.48). While clear guidelines have been laid out for hate speech, fear speech is not moderated as of now.

We particularly focus on understanding the dynamics of fear speech against Muslims in the public WhatsApp groups. Encrypted platforms like WhatsApp, where, unlike open platforms like Facebook or Twitter, there is no content moderation, facilitate the spread and amplification of these messages. The situation is particularly dangerous in large political groups, which are typically formed by like-minded individuals who offer no resistance or countering to fear speech messages. Such groups have been used to target the Muslim community several times.7

Following the data collection strategy from Garimella et. al [24], we collected the data from over 5,000 such groups, gathering more than 2 million posts. Using this data, we manually curated a dataset of 27k posts out of which ~ 8,000 posts were fear speech and ~ 19,000 were non fear speech. Specifically, we make the following contributions:

- For the first time, our work quantitatively identifies the prevalence and dynamics of fear speech at scale, on WhatsApp, which is the most popular social media in India.
- We do this by curating a large dataset of fear speech. The dataset consists of 7,845 fear speech and 19,107 non fear speech WhatsApp posts. The dataset will be made public after the completion of the review process of the paper.
- We develop models that can automatically identify messages containing fear speech.
- Finally, using a novel, privacy preserving approach, we perform an online survey using Facebook ads to understand the characteristics of WhatsApp users who share and consume fear speech.

Our study highlights several key findings about fear speech. We observe that the fear speech messages have different properties in terms of their spread (fear speech is more popular), and content (deliberately focusing on specific narratives to portray Muslims negatively). Next, we focus on users posting fear speech messages and observe that they occupy central positions in the network, which enables them to disseminate their messages better. Using Facebook ads survey, we observe that users in fear speech groups are more likely to believe and share fear speech related statements and are more likely to take anti-Muslim stance on issues. We further develop NLP models for automatic fear speech classification. We find that even the state-of-the-art NLP models are not effective in the classification task.

2 RELATED WORK

Speech targeting minorities has been a subject of various studies in literature. In this section we first look into previous research that deals with various types of speech and highlight how fear speech is different from them.

**Hate speech.** Extreme content online is mostly studied under the hood of hate speech. Hate speech is broadly defined as a form of expression that “attacks or diminishes, that incites violence or hate against groups, based on specific characteristics such as physical appearance, religion, descent, national or ethnic origin, sexual orientation, gender identity or other,and it can occur with different linguistic styles, even in subtle forms or when humour is used” [22]. Most of the research in this space has looked into building models for detection of hate speech [3, 69], characterising it [46], and studying counter-measures for hate speech [17, 64]. However, most studies use their own definition of hate speech and the lack of a single definition makes it a difficult annotation task [56] and subject to abuse.

1https://www.huffingtonpost.in/entry/whatsapp-hate-muslims-delhi_in_5d43012ae6b0ac57fc9e0d80
For instance, there are multiple incidents where governments used vague definitions of hate speech to create laws against free speech to punish or silence journalists and protesters [11, 12, 66]. In recent years, there has been a push by researchers to look into specific definitions of hate speech like dangerous speech and fear speech so that hate speech can be tackled at a more granular level [23].

**Dangerous speech.** One of the sub-fields, dangerous speech [9] is defined as an expression that “have a significant probability of catalyzing or amplifying violence by one group against another, given the circumstances in which they were made or disseminated”. The main challenge about dangerous speech is that it is very difficult to assess whether a statement actually causes violence or not. The authors provide various other factors like the speaker, the environment, etc. as essential features to identify dangerous speech. These features are largely anonymously in the online world.

**Fear speech.** In their paper Benesch [9], defined fear as one of the features of dangerous speech. Klein [36] et al. claim that a large amount of discussion on race on platforms like Twitter is actually inflected with fear rather than hate speech in the form of content such as  #WhiteGenocide, #Blackcrimes, #AmericaUnderAttack. A recent UNESCO report even argues that fear speech can also facilitate other forms of harmful content. However, fear speech was formally defined by Buyse [15] et al as an expression that attempts to instill a sense of fear in the mind of the reader. Though it cannot be pinpointed if fear speech is the cause of the violence, it lowers the threshold to violence. Most of the work in this space is based in social theory and qualitatively looks at the role of fear as a technique used in expressing hatred towards a (minority) community. Our work on the other hand, is the first that looks at fear speech at scale quantitatively.

**Islamophobia.** Another aspect relevant to our study is the study of Islamophobia on social media. Dictionary definition of Islamophobia refers to fear of Muslim community, but over time, studies on Islamophobia have also covered a broad range of factors including, hate, fear and threat against the Muslim community. There are various works studying the problem at scale, most of them covering the hate side of the domain [67]. The perspective of fear in Islamophobia is well-established but there is very less work studying this issue [28]. One of the works have tried to establish the difference between direct hate speech and indirect fear speech against Muslims [63] but it is mostly a limited case study. Our work can be considered studying the fear component of Islamophobia, but our framework for annotating and characterizing fear speech can be used to study fear speech targeted toward other religious or ethnic groups.

**WhatsApp.** WhatsApp could be a good target for bad actors who want to spread hatred towards a certain community at scale. On platforms like Twitter and Facebook, the platforms can monitor content being posted and hence provide content moderation tools and countering mechanisms in place like suspension of the user and blocking of the post for limiting the use of harmful/hateful language. WhatsApp, on the other hand, is an end-to-end encrypted platform, where the message can be seen only by the end users. This makes the spread of any form of harmful content in such platforms much easier.

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1. https://en.unesco.org/news/dangerous-speech-fuelled-fear-cries-can-be-countered-education
2. https://en.wikipedia.org/wiki/Islamophobia

For this study, we focus on the public WhatsApp groups which discuss politics. These groups only make up a small fraction of the overall conversations on WhatsApp, which are private. However, political groups on WhatsApp are extremely popular in countries like India and Brazil [42] and have been used to target minorities in the past. The Supreme Court of India has held WhatsApp admins liable for any offensive posts found in groups they manage. Such strict laws could be a reason for the cautious nature of the users about spreading offensive and deliberately hateful posts in public groups and instead opt for subtle fear speech which is indirect.

Garimella and Tyson [26] performed one of the earliest work on WhatsApp, where they devised a methodology to extract data from public WhatsApp groups. Following a similar strategy, other works have studied political interaction of users in various countries like India [16, 52], Brazil [16] and Spain [59]. The other part of research on WhatsApp studies the spread of misinformation [25, 51] in the platform. While, misinformation is a nuanced problem, Arun [5] argues that content that has an intent to harm (for e.g., hate speech or fear speech) is more dangerous. Currently, there is no work that studies hateful content both explicitly or implicitly on WhatsApp at scale.

### 3 DATASET

In this section, we detail the data collection and processing steps that we undertook. Our analysis relies on a large dataset obtained from monitoring public groups on WhatsApp.

#### 3.1 Data collection

In this paper, we use the data collected from public WhatsApp groups from India discussing politics which usually have a huge interplay with religion [8, 37]. In order to obtain a list of such public WhatsApp groups we resorted to lists publicized on well-known websites or social media platforms such as Facebook groups. Due to the popularity of WhatsApp in India, political parties massively create and advertise such groups to spread their party message. These groups typically contain activists and party supporters, and hence typically act as echo chambers of information. Surveys show that one in six users of WhatsApp in India are a member of one of such public groups [42].

We used the data collection tools developed by Garimella and Tyson [26] to gather the WhatsApp data. With help from journalists who cover politics, we curated lists of keywords related to politicians and political parties. Using this list we looked up public WhatsApp groups on Google, Facebook and Twitter using the query ”chat.whatsapp.com + query”, where query is the name of the politician or political party. The keyword lists cover all major political parties and politicians all across India in multiple languages. Using this process, we joined and monitored over 5,000 political groups discussing politics. From these groups, we obtained all the text messages, images, video and audio shared in the groups. Our data collection spans for around 1 year, from August 2018 to August 2019. This period includes high profile events in India, including the
national elections and a major terrorist attack on Indian soldiers. The raw dataset contained 2.7 million text messages.

3.2 Pre-processing

The dataset contains over a dozen languages. To make it easier to annotate, we first filtered posts by language to only keep posts in Hindi and English, which cover over 70% of our dataset. Next, we applied simple techniques to remove spam. We randomly sampled 100 messages and manually found that 29% of them were spam. These spam messages include messages asking users to sign-up for reward points, offers, etc., phishing links, messages about pornography, and click-baits. To filter out these messages, we generated a set of high precision lexicon that can suitably remove such messages. Since the spam removal method is based on a lexicon, it is possible that some spam messages are missed. To cross-check the quality of the lexicon, after the cleaning, we randomly sampled 100 data points again from the spam-removed dataset and only found 3 spam messages. Detailed statistics about this spam filtered dataset are reported in Table 2.

Table 2: Characteristics of our dataset.

| Features               | Count     |
|------------------------|-----------|
| #posts                 | 1,426,482 |
| #groups present        | 5,010     |
| #users present         | 109,542   |
| average users per group | 30        |
| average messages per group | 284      |
| average length of a message (in words) | 89 |

Since messages contain emojis, links, and unicode characters we had to devise a pre-processing method that is capable of handling such variety of cases. For our analysis, we not only use the text messages, but also the emoji and links. So, we develop a pre-processing method which can extract or remove the particular entities in the text messages as and when required. When doing text analysis we remove the emojis, stop words and URLs using simple regular expressions. Further, to tokenize the sentences we lowercase the English words in the message and use a multilingual tokenizer from CLTK [33], as a single message can contain words from multiple languages. For emoji and URL analysis we extract the particular entities using specific extractors for these entities.

3.3 Generating lexicons

We use lexicons to identify the targets in a message. Since, we are trying to identify fear speech against Muslims we build a lexicon related to Muslims. At first, we create a seed lexicon which has words denoting Muslims for e.g Muslims, Musalman (in Hindi). Next, we tokenize each post in the dataset with the method mentioned in the pre-processing section into a list of tokens. Since the words representing a particular entity may contains n-grams, we consider an n-gram generator — Phrase — to convert the list of tokens (unigrams) to n-grams. We consider only those n-grams which have a minimum frequency of 15 in the dataset and restrict n to 3. Thus, each sentence gets represented by a set of n-grams where n can be 1, 2 or 3. The entire corpus in the form of tokenized sentences is used to train a word2vec model with default parameters. We bootstrap each of the seed lexicon using the word2vec model. For each word/phrase in a particular seed lexicon we generate 30 similar words/phrase based on the embeddings from the word2vec model. We manually select the entity specific words and add them to the seed lexicon. Next this modified seed lexicon is again considered as the seed lexicon, and we redo the former steps. This loop continues until we are unable to find any more keywords to add to the lexicon. This way we generate the lexicon for identifying messages related to Muslims. The lexicon thus obtained can be found at this url.

4 ANNOTATING MESSAGES FOR FEAR SPEECH

We filtered our dataset for messages containing the keywords from our lexicon and annotated them for fear speech. The annotation process enumerates the steps taken to sample and annotate fear speech against Muslims in our dataset.

4.1 Annotation guidelines

We follow the fear speech definition by Buyse et. al [15] for our annotation process. In their work, fear speech is defined “as a form of expression aimed at instilling (existential) fear of a target (ethnic or religious) group”. For our study, we considered the Muslims as the target group. In order to help and guide the annotators, we provide several examples highlighting different forms where they might find fear speech. These forms include but are not limited to (a) fear induced by using examples of past events, e.g., demolition of a temple by a Mughal ruler, (b) fear induced by referring to present events, e.g., Muslims increasing their population at an increasing rate. (c) fear induced by cultural references, e.g., verses from the Quran, interpreted in a wrong way. (d) fear induced by speculation of dominance by the target group, e.g., members of the Muslim community occupying top positions in government institutions and the exploitation of Hindus. Figure 1 shows the detailed flowchart used for the annotation process. Note that our annotation guidelines are strict and focused on a high precision annotation. Further, we asked the annotators to annotate a post as fear speech even if only a part of the post appear to induce fear. This was done because many of the posts were long (as we see in Table 2, the average message has 89 words) and contained non fear speech aspects as well.

4.2 Annotation training

The annotation process was led by two PhD students as expert annotators and performed by seven under-graduate students who were novice annotators. All the undergraduate students study computer science, and were voluntarily recruited through a departmental

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13The lexicon can be found here: https://www.dropbox.com/s/yfodqdupc/spam_filtered_keywords.txt?dl=0
14https://github.com/lipoja/URLExtract
15https://github.com/carpedm20/emoji/
16https://radimrehurek.com/gensim/models/phrases.html
17https://radimrehurek.com/gensim/models/word2vec.html
18https://www.dropbox.com/s/remodygggmyb6/muslim_keywords.txt?dl=0
19https://thewire.in/communalism/sudarshan-news-tv-show-upsc-jihad-suresh-chavhanke-fact-check
The text is NOT FEAR SPEECH

SPEECH (1)

was deployed on a Heroku instance. Each annotator was given a

After the training process, we proceeded to the main annotation task

To check the effect of the first round of training, we sampled an-

tation task we used the open source platform Docanno

lexicon and gave them to the annotators in batches. For this anno-

by sampling posts having at least one keyword from the Muslim

4.3 Main annotation

After the training process, we proceeded to the main annotation task

In order to train the annotators we needed a gold-label dataset.

For this purpose the expert annotators annotated a set of 500 posts

Later the expert annotators discussed the annotations and resolved

The text is NOT FEAR SPEECH

FEAR SPEECH (2)

The text is NOT

F E A R SPEECH

The text is FEAR

SPEECH (3)

Yes

NO

NO

YES

Does this induce a fear
against the Muslim
community?

NO

YES

NO

YES

The text is NOT FEAR SPEECH

FEAR SPEECH (4)

The text is FEAR

SPEECH

Figure 1: A step-by-step flowchart used by annotators to an-
notate any post as fear speech or non fear speech.

email list and compensated through an online gift card. Both the

In order to train the annotators we needed a gold-label dataset.

For this purpose the expert annotators annotated a set of 500 posts

using the annotation guidelines. This set was selected by using the

threshold of having at least one keyword from the Muslim lexicon.

Later the expert annotators discussed the annotations and resolved

the differences to create a gold set of 500 annotations. This initial

set had 169 fear speech and 331 non fear speech post. From this set

we sampled a random set of 80 posts initially for training the anno-

tators. This set contained both the classes in equal numbers. After,

the annotators finished this set of annotations we discussed the

incorrect annotations in their set with them. This exercise further

trained the annotators and fine-tuned the annotation guidelines.

To check the effect of the first round of training, we sampled an-

other set of 40 examples each from both classes again from the

set of 500 samples. In the second round, most of the annotators

could correctly annotate at least 70% of the fear speech cases. The

novice annotators were further explained about the mistakes in

their annotations.

4.3 Main annotation

After the training process, we proceeded to the main annotation task

by sampling posts having at least one keyword from the Muslim

lexicon and gave them to the annotators in batches. For this anno-

tation task we used the open source platform Docanno\(^{30}\), which was

deployed on a Heroku instance. Each annotator was given a

secure account where they could annotate and save their progress.

Each post was annotated by three independent annotators. They

were instructed to read the full message and based on the guidelines

provided, select the appropriate category (either fear speech or not).

We initially started with smaller batches of 100 posts and later

increased it to 500 posts as the annotators became well-versed with

the task. We tried to maintain the annotators’ agreement by sharing

few of the errors in the previous batch. Since fear speech is highly

polarizing and negative in nature the annotators were given ample

time to do the annotations.

While there is no study which tries to determine the effect of

fear speech annotations on the annotators, there are some evidence

which suggest that the exposure to online abuse could lead to

negative mental health issues [40, 68]. Hence, the annotators were

advised to take regular breaks and not do the annotations in one

sitting. Finally, we also had regular meetings with them to ensure

the annotations did not have any effect on their mental health.

4.4 Final dataset

Our final dataset consists of 4,782 posts with 1,142 unique messages

labeled as fear speech and 3,640 unique messages labeled as not

fear speech. We achieved an inter-annotator agreement of 0.36

using Fleiss \(\kappa\) which is better than the agreement score on other

related hate speech tasks [18, 48]. We assigned the final label using

majority voting.

Next, we used locality sensitive hashing [27] to find variants

and other near duplicate messages of the annotated message in the

dataset. Two documents were deemed to be similar if they have

at least 7 hash-signatures matching out of 10. A group of similar

messages following the former property will be referred to as shared

message, henceforth. We manually verified 100 such messages and

their duplicates and found error in 1% of the cases. This expanded

our fear speech to \(\sim 8,000\) messages spread across \(\sim 1,000\) groups

and spread by \(\sim 3,000\) users. Detailed statistics of our annotated

dataset are shown in Table 3. Note that this dataset is quite different

in its properties from the regular dataset shown in Table 2, with

the average message being 5 times longer.

We observe that the non fear speech messages contain information

pertaining to Quotes from Quran, political messages which talk about

Muslims, Madrasa teachings and news, Muslim festivals etc. An excerpt from one of the messages “... Who is God? One of the

main beauties of Islam is that it acknowledges the complete perfection

greatness and uniqueness of God with absolutely no compromises....”

Ethics note: We established strict ethics guidelines throughout

the project. The Committee on the Use of Humans as Experimen-

tal Subjects at MIT approved the data collection as exempt. All

personally identifiable information was anonymized and stored

separately from the message data. Our data release conforms to

the FAIR principles [65]. We explicitly trained our annotators to

be aware of the disturbing nature of social media messages and to

take regular breaks from the annotation.

5 ANALYSIS

We use the dataset in Table 3 to characterise fear speech at two

levels: message level and user level. To further understand the

user behaviour, we also conducted a survey among the WhatsApp

group members to understand their perception and beliefs about

fear speech. To measure statistical significance, we perform Mann-

U-Whitney tests [44], which is known to be stable across sample

\(^{30}\)https://github.com/doccano/doccano
size differences. Error bars in the plots represent 95% confidence intervals.

5.1 Message characteristics

In this section, we investigate the spread and dynamics of fear speech messages.

Spread characteristics. First, we compute the characteristics related to the spread of messages, like the number of shares. In Figure 2(a), we observe that fear speech messages are shared more number of times on average as compared to non-fear speech messages. We also observe that these fear speech messages are spread by more number of users and sent to more groups on average (Figure 2(b) & Figure 2(c), respectively). Next, we compute the lifetime of a message as the time difference (in days) between the first and the last time the message was shared in our dataset. We observe that the lifetime of a fear speech message is more than that of a non fear speech message. All the differences shown in Figure 2 are statistically significant. We also consider the fact that our dataset may be prone to right censoring i.e. the messages appearing close to the ending timestamp may reappear again. Hence, we consider all the messages appearing after June 2019 as message which can reappear a.k.a unobserved data. With the rest of the data, we trained survival functions [29] for fear speech and non fear speech messages. Log rank test [45] on both the functions are significantly different ($p < 0.0001$).

These results suggest that fear speech, through its strong narratives and arguments, is able to bypass the social inhibitions of users and can spread further, faster and last longer on the social network.

Empath analysis. Next, we perform lexical analysis using Empath [21], a tool that can be used to analyze text in over 189 pre-built lexical categories. First, we select 70 categories ignoring the topics irrelevant to fear speech for e.g. technology and entertainment. One this set of 70 categories, we characterize the english-translated version of the messages over these categories and report the top 10 significantly different categories in Figure 3. Fear speech scores significantly high in topics like 'hate', 'crime', 'aggression', 'suffering', 'fight', and 'negative emotion (neg_emo)' and 'weapon'. Non fear speech scored higher on topics such as 'giving', 'achievement' and 'fun'. We use Mann-Whitney U [44] test and show the significance levels *** ($p < 0.0001$), ** ($p < 0.001$), * ($p < 0.01$) for each of the category.

Figure 2: Characteristics of fear speech messages: (a) average number of times a message was shared ($p < 0.001$), (b) average number of users who shared a message ($p < 0.0001$), (c) average number of groups the message was shared to ($p < 0.0001$), and (d) average number of days the message is active ($p < 0.0001$).

Figure 3: Lexical analysis using Empath. We report the mean values for several categories of Empath. Fear speech scored significantly high on topics like 'hate', 'crime', 'aggression', 'suffering', 'fight', and 'negative emotion (neg_emo)' and 'weapon'. Non fear speech scored higher on topics such as 'giving', 'achievement' and 'fun'. We use Mann-Whitney U [44] test and show the significance levels *** ($p < 0.0001$), ** ($p < 0.001$), * ($p < 0.01$) for each of the category.

methods explained earlier, we first clean numbers and URLs in the text. For each emoji, we add a space before and after it to separate the emojis which were joined. To get more meaningful topics, we use Phraser\(^2\) to convert the list of tokens (unigrams) to bi-grams. We then pass the sentences (in the form of bi-grams) through the LDA model. To select the number of topics, we used the coherence score [54] from 2 to 15 topics. We found that 10 topics received

| Features                      | FS     | NFS    |
|-------------------------------|--------|--------|
| #posts                        | 7,845  | 19,107 |
| #unique posts                 | 1,142  | 3,640  |
| #numbers of groups            | 917    | 1541   |
| #number of users              | 2,933  | 5,661  |
| Average users per group       | 70     | 60     |
| Average length of a message (in words) | 500    | 464    |

Table 3: Statistics of fear speech (FS) and non fear speech (NFS) in the annotated data.

2https://radimrehurek.com/gensim/models/phrases.html
the highest coherence score of 0.45. Hence we used 10 topics for the LDA. Two of these topics were political and irrelevant to fear speech and hence ignored thus making 8 topics overall.

Out of the topics selected, we clearly see a notion to promote negative thoughts toward the Hindu community portraying that they might be inciting disharmony across the nation. They discuss and spread various Islamophobic conspiracies around Muslims being responsible for communal violence (Topic 4, 7), to Muslim men promoting inter faith marriage to destroy the Hindu religion (Topic 5). One of the topics also indicate exploitation of Dalits by the Muslim community (Topic 6). In the annotated dataset, we found that Topic 6 and 7 were the most prevalent ones with 18% of the posts belonging to each. The lowest number of posts (7%) was found for Topic 5.

**Emoji usage.** We observe that 52% of the fear speech messages had at least one emoji present in them, compared to 44% messages if we consider the whole data. Our initial analysis revealed that emojis were used to represent certain aspects of the narrative. For example, 🇮🇳 was used to represent the Hindutva (bhagwa) flag\(^2\), 🕔 to represent purity in Hinduism\(^2\), 🧵 were used to demonize Muslims and 🦊 were used to represent the holy book of Islam, the Quran. Further, these emojis also tend to frequently occur in groups/clusters. In order to understand their usage patterns we cluster the emojis. We first form the co-occurrence network \(^{41}\) of emojis where the nodes are individual emojis and edges represent that they co-occur within a window of 5 characters at least once. The weight \((W)\) of the edge is given by the equation 1, where \(F_{ij}\) represents the number of times the emojis \(i\) and \(j\) co-occur within a window of 5 and \(F_{i}\) represents the number of times emoji \(i\) occurs.

\[
W_{ij} = \frac{F_{ij}}{(F_{i} * F_{j})}
\]

After constructing this emoji network, we used the Louvain algorithm \(^{13}\) to find communities in this network. We found 10 communities out of which we report the four most relevant communities in Table 5.

We manually analyzed the co-occurrence patterns of these emojis and found several interesting observations. Emojis such as 🇮🇳, 🕔, 🧵, 🦊, 🧵 were used to represent the Hindutva ideology (row 1). Another set of emojis 🧵, 🧵, 🧵, 🧵, 🧵 (row 2) was used to represent the Muslim community in a negative way. The former example helps in strengthening the intra-group (among members of the Hindu community) ties and the latter example vilifies the Muslim community as monsters or animals \(^{15}\).

**Toxicity.** While qualitatively looking at the fear speech data, we observed that fear speech was usually less toxic in nature as compared to hate speech. To confirm this empirically, we used a recent hate speech dataset \(^{7}\) and compared its toxicity with our dataset. Since targets of the posts were not annotated in the data, we used the English keywords in our Muslim lexicon to identify the hate speech targeting Muslims. Overall we found 155 hateful posts where one of the keywords from our lexicon matched. We passed the fear speech, non fear speech and hate speech subset dataset through the Perspective API \(^{1}\), which is a popular application for measuring toxicity in text. In Figure 4, we observe that average toxicity of hate speech is higher than that of fear speech (\(p\)-value < 0.001). Average toxicity of non fear speech is closer to fear speech. This shows how nuanced the problem at hand is and, thereby, substantiates the need for separate initiatives to study fear speech. In other words, while fear speech is dangerous for the society, the toxicity scores seem to suggest that the existing algorithms are not fine-tuned for their characterization/detection/mitigation.

To further establish the observation, we used a hate lexicon specific to Indian context \(^{14}\) and measured its ability to detect fear speech. We assigned a fear speech label for all the posts in our dataset where one or more keywords from the hate lexicon matched. Considering these labels as the predicted label, we got an F1 score of 0.53. Using a pre-trained hate speech detection model \(^{3}\) and predicting the labels, also did not help as the pre-trained model performed more poorly (0.49). This clearly points out the need of novel mechanisms for the detection of fear speech.

Figure 4: Toxicity comparison based on perspective api.

### 5.2 User characterization

In this section, we focus on the ~ 3,000 users who posted at least one of the fear speech messages to understand their characteristics. Figure 5 shows the distribution of fear speech messages among the users. While most of these users post fear speech once or twice, there is a non-zero fraction of users who post 50+ times. Further only 10% users posts around 90% messages as shown in the inset of Figure 5. This indicates that there could be a hub of users dedicated for spawning such messages. We attempt to substantiate this through the core-periphery analysis below.

**Core-periphery analysis.** To understand the network positions of the fear speech users, we constructed a user-user network where there is link between two users if both of them are part of at least one group. The weight of the edge between two users represents the number of groups both of them are part of. This way we formed a network consisting of 109,292 nodes and 6,382,883 edges. To obtain a comparative set of users similar to the fear speech users, we sample a control set from the whole set of users (except the fear speech users) using propensity based matching \(^{55}\). For matching we use the following set of features (a) avg. number of messages per month, (b) std. deviation of messages per month, (c) month the group had its first message after joining, and (d) the number of months the group had at least one message. We further measure the statistical significance between the fear speech users and the matched non fear speech users and found no significant difference (\(p > 0.5\)).

Next, we utilize k-core or coreness metric \(^{62}\) to understand the network importance of the fear speech and non-fear speech...
Table 4: List of topics discussed in fear speech messages.

| Topic # | Words                                                                 | Name                                                                 |
|---------|----------------------------------------------------------------------|----------------------------------------------------------------------|
| 1       | will kill, mosque, kill you, quran, 🌞, 🌞, 🔥, love jihad, 🌞, her colony, ramalingam, 🌞, 🌞, crore, cattle, if girl, cleric, bomb bang, 😱, children, war | Women mistreated in Islam                                             |
| 2       | group, hindu brother, bengal, 🌞, temple, terrorist, rape, killing, zakat foundation, peoples, book hadith, page quran, vote, police, quran, against, indian, dalits, khwaja, story | UPSC jihad (Zakat foundation)                                         |
| 3       | akbar, police, the population, 🌞, islamic, society, war, gone, rape, population, children, family, love jihad, type, islamic, become | Muslim population                                                     |
| 4       | sri lanka, abraham, congress, love jihad, daughter, league, grandfather grandmother, university, family, girl, between, jats, i am scared, love, all, children, fear, pakistani, terrorist, 🔥🔥, without, 😱 | Sri Lanka Riots                                                       |
| 5       | temple smashed, answer, rape, 😱, questions, gone, 🌞🌞, wrote, clean, girls, modi, woman, book hadith, hindu, whosoever won, will give, work, 😱, 😱, ↻, ↻, robbery | Love jihad                                                            |
| 6       | congress, 🔥, type, about, savarkar, vote, dalit, indian, will go, islamic, he came, somewhere, our, leader, will do, terrorist, war, born, person, against, effort | Muslim exploitation of dalit                                           |
| 7       | village, temple, kerala, quran, stay, become, mewat, history, between, congress, quran sura, family, mopsy, rape, christian, sheela, dalit, living, om sai, 🌞🌞, love jihad, earth, come, start | Kerala riots                                                          |
| 8       | congress, marathas, girl, delhi, kill, asura import, jihadi, 🔥, master, janet levy, gives, mother father, surf excel, temple, 🌞🌞, daughter, pigs, terrorists, maratha, century | Islamization of Bengal                                                |

Table 5: Top communities constructed using the Louvain algorithm from the emoji co-occurrence graph. Interpretation of the emojis as observed manually are added alongside each of the emoji communities.

| Row | Emojis | Interpretation                                |
|-----|--------|-----------------------------------------------|
| 1   | 🌞🌞🌞 | Hindutva symbols                              |
| 2   | ☪️ ☪️ | Muslim as demons                              |
| 3   | ⚡️ ⚡️ | Terrorist attacks or riots by Muslims         |
| 4   | 😱 😱 | Angry about torture on Hindus                 |

Figure 5: Distribution of fear speech messages posted by the fear speech users. Inset shows a CDF with cumulative % of messages generated on the y-axis and user rank (converted to %) on x-axis.

Figure 6 shows the cumulative distribution of the core numbers for the fear and the non fear speech users, respectively. We observe that the fear speech users are occupying far more central positions in the network, as compared to non fear speech users ($p$-value $< 0.0001$ with small effect size [39] of 0.20). This indicates that some of the fear speech users constitute a hub-like structure in the core of the network. Further, 8% of these fear speech users are also admins in the groups where they post fear speech.

Figure 6: Cumulative distribution of $k$-core numbers for fear speech (FS users) and non fear speech users (NFS users). We see that FS users have a lower core number (higher centrality). The differences are significant at ($p < 0.0001$). A zoomed inset further highlights the difference between the two curves.

5.3 Survey to characterize users

In order to characterize users who share or consume fear speech, we used a novel, privacy preserving technique to survey our WhatsApp user set. We used the Custom Audience targeting feature provided
In 1761, Afghanistan got separated from India to become an Islamic nation. Around 10,000 users from the top 100 groups posted the most fear speech, and, a controlled set of users who neither posted any fear speech nor were part of a group where it was posted in our dataset (UNFSG, around 10,000 users from a random sample of 100 groups which do not post any fear speech). Only roughly 50% of these users had Facebook accounts with a matching phone number and were eligible for the advertisements to be shown. We showed an ad containing a link to the survey (hosted on Google Forms). The survey was short and took at most 3 minutes of a user’s time. No monetary benefits were offered for participating. An English translation of the ad that was used is shown in Figure 7.

The survey was a 3x2 design: the three user sets presented with 2 types of statements: fear speech and non fear speech. In total, we chose 8 statements — 4 containing carefully chosen snippets from fear speech text in our dataset and 4 statements containing true facts. To avoid showing overly hateful statements, we paraphrased the fear speech messages from our dataset to show a claim, e.g., ‘In 1761, Afghanistan got separated from India to become an Islamic nation’. The participants were asked whether they believed in the statement, and if they would share the statements on social media. Along with the core questions, we had two optional questions about their gender and the political party they support. Finally, to obtain a baseline on the beliefs of the various groups of users about Muslims, we asked 2 questions on their opinion about recent high profile issues involving Muslims in India. These include their opinion about (a) the Citizen Amendment Bill and (b) the Nizamuddin Markaz becoming a COVID-hotspot [10]. All the participants were shown fact checks containing links debunking the fear speech statements at the end of the survey. To keep the survey short per user, we split the 8 statements into two surveys with four statements per survey with two being from the fear speech set and the other two being from the non fear speech set of our dataset.

The ads ran for just under a week, and we received responses from 119 users. The low response rate (around 1%) is expected and was observed in other studies using Facebook ads to survey users [32] without incentives. A majority of the respondents (85%) were male. Among the rest 5% were female and 10% did not disclose their gender.

We begin with analyzing the results of the survey based on the beliefs about fear speech statements. Figures 8 shows the beliefs of the three groups of users for the two types of statements containing fear speech (FS) and not containing fear speech (NFS). We see that users belonging to UPFG and UFSG have a higher probability of either weakly or strongly believing fear speech statements than non-fear speech statements. The trends are reversed when looking at the UNFSG set. Similarly, Figure 9 shows trends for whether the users will share statements containing fear speech or not and it clearly shows that users in UPFG and UFSG are more likely to share fear speech. Note that due to the low sample size, the results are not statistically significant and hence, no causal claim can be made. However, the trends in multiple user sets show some evidence that users getting exposed are consistently more likely to believe and share fear speech statements. Further analysis on a larger sample might help attain a significant difference.

Finally, we also looked at baseline questions on the beliefs about issues related to Muslims in India conditioning on the group of the users. The results are shown in Table 6. We see clear evidence that the users who belong to UPFG and UFSG are significantly more likely to support the right wing party in power (BJP), blame Muslims for the COVID-19 hotspot in Nizamuddin Markaz, and to support the Citizenship Amendment Bill. There is no consistent trend between users who are just a part of a group where fear speech is posted vs. users who post fear speech.

Even though the response rate to our survey was small, the overall paradigm of being able to create and launch surveys conditioned...
on prior observational data is quite powerful and can be useful in providing valuable insights complementing many social media datasets.

Figure 8: Belief toward fear speech (FS) and non fear speech (NFS) of users in the set (i) users posting fear speech (UPFG), (ii) users in fear speech groups (UFSG), and (iii) users in non fear speech groups. Error bars show 95% confidence intervals.

Figure 9: Sharing propensity for fear speech (FS) and non fear speech (NFS) by the users in the set (i) users posting fear speech (UPFG), (ii) users in fear speech groups (UFSG), and (iii) users in non fear speech groups.

5.4 Summary of insights

Overall, the analysis in this section reveals several insights into the usage of fear speech in Indian WhatsApp public groups. Our analysis proceeded along two dimensions: content and users.

We observed that the fear speech messages have a higher spread and larger lifetime when compared to non fear speech messages. The fear speech messages talk about topics such as ‘aggression’, ‘crime’, ‘hate’, ‘fighting’ and ‘negative emotions’ in general. Using topic modeling, we found that there are concerted narratives which drive fear speech, focused on already debunked conspiracy theories showcasing Muslims to be criminals and Hindus to be victims. We showcased the prevalence and use of various emojis to emphasize the several aspects of the message and dehumanize Muslims. Finally, when compared to hate speech, fear speech is found to be significantly less toxic.

We then looked users who posted fear speech messages and found that these users are popular and occupy central positions in the network, which in part explains the popularity of the fear speech content, allowing them to disseminate such messages much more easily. Using a survey of these users, we show that fear speech users are more likely to believe and share fear speech related statements and significantly believe or support in anti-Muslim issues.

6 AUTOMATIC FEAR SPEECH DETECTION

In this section, we develop models for automatic detection of fear speech. We tested a wide range of models for our use case.

Classical models. We first used Doc2Vec embeddings [38] with 100 dimensional vectors to represent a post. We use Logistic Regression and SVM with RBF kernel as the classifier.

LASER-LSTM: In these, we decomposed the paragraphs into sentences using a multilingual sentence tokenizer [33]. Then we used LASER embeddings to represent the sentences [4] which produces a sentence embedding of 1024 dimension per sentence. These sequences of sentence representations were then passed through a LSTM [36] model to get a document level representation. Then fully connected layer was used to train the model. For the LSTM, we set hidden layer dimension to 128 and used the Adam optimizer [34] with a learning rate of 0.01.

Transformers: Transformers are a recent NLP architecture which are formed using a stack of self-attention blocks. There are two models in the transformers, which can handle multilingual posts – multilingualBERT [19] and XLM-Roberta [57]. Both of them are limited in the number of tokens they can handle (512 at max). We set the number of tokens $n = 256$ for all the experiments due to system limitations. We used tokens from different parts of the sentences for the classification task [2]; these are (a) $n$-tokens from the start, (b) $n$-tokens from the end, and, (c) $(\frac{n}{2})$-tokens from the start and $(\frac{n}{2})$-tokens from the end append together by a <SEP> token. For optimization, Adam optimizer [34] was used with a learning rate of $2e^{-5}$.

All the results are reported using the 5-fold cross validation. In each fold, we train on the 4 splits, use 1 split for validation. The details of the performance of various models on the validation set are reported in Table 7. We select the top performing model — XLM-Roberta + LR (5th row) based on the AUC-ROC score (0.83). This metric is deemed effective in many of the past works [50, 58], as it is not affected by the threshold. In order to get an idea of the prevalence of fear speech in our dataset we used the best model and ran inference on the posts having Muslim keywords. In total, we got around 18k fear speech out of which 12k were unique. Since the model was not very precise (precision 0.51) when detecting the fear speech class, we did not proceed with further analysis on predicted data. The lower precision of the most advanced NLP models (while detecting fear speech), leaves ample scope for future research.

In order to investigate further, we extract all the data points where the model’s prediction was wrong. Then we randomly sampled 200 examples from this set and passed them through LIME [53] — a model explanation toolkit. Each post was passed through LIME. LIME returns the top words which affected the classification. We observed this top words per post to identify if there exist any prominent patterns among the wrong predictions. We noted two important patterns, which were recurrent — (a) the model was predicting the wrong class based on confounding factors (CF) for, e.g., stop words in Hindi/English, (b) in few other cases, the models were able to base their predictions on the target (Muslims) but failed to...
Table 7: Model performance on the task of classification of fear speech. For each column best performance is shown in bold and the second best is underlined.

| Model                        | Features                  | Accuracy | F1-Macro | AUC-ROC | Precision (FS) |
|------------------------------|---------------------------|----------|----------|---------|----------------|
| Logistic regression          | Doc2Vec                   | 0.72     | 0.65     | 0.74    | 0.44           |
| SVC (with Rf kernel)         | Doc2vec                   | 0.75     | 0.69     | 0.77    | 0.49           |
| LSTM                         | LASER embeddings          | 0.66     | 0.63     | 0.76    | 0.39           |
| XLM- Roberta + LR            | Raw text (first 256 tokens) | 0.70     | 0.65     | 0.82    | 0.42           |
| XLM- Roberta + LR            | Raw text (first 128 and last 128) | 0.76     | 0.71     | 0.83    | 0.51           |
| XLM- Roberta + LR            | Raw text (last 256 tokens) | 0.72     | 0.68     | 0.81    | 0.45           |
| mBERT + LR                   | Raw text (first 256 tokens) | 0.70     | 0.65     | 0.80    | 0.45           |
| mBERT + LR                   | Raw text (first 128 and last 128) | 0.72     | 0.65     | 0.80    | 0.48           |
| mBERT + LR                   | Raw text (last 256 tokens) | 0.67     | 0.63     | 0.79    | 0.42           |

Table 8: Examples where the model could not predict the ground truth (GT) and type of error that happened (CF or TNE). We also show the top words (highlighted in yellow) which affected the classification (as returned by LIME).

| Text (translated from Hindi) | GT and TE      | FS and CF | FS and TNE |
|------------------------------|----------------|-----------|-----------|
| Big breaking: Dharmendra Shinde, a marriageist Hindu brother, was murdered by Muslims for taking out the procession of Dalit teens from the mosque … Mr. Manoj Parmar reached Pipalara and showed communal harmony and prevented the atmosphere from deteriorating as well as taking appropriate action against the accused … There is still time for all Hindus to stay organized, otherwise, India will not take much time to become Pakistan. Share it as much as the media is not showing it. | Big breaking: Dharmendra Shinde, a marriageist Hindu brother, was murdered by Muslims for taking out the procession of Dalit teens from the mosque … Mr. Manoj Parmar reached Pipalara and showed communal harmony and prevented the atmosphere from deteriorating as well as taking appropriate action against the accused … There is still time for all Hindus to stay organized, otherwise, India will not take much time to become Pakistan. Share it as much as the media is not showing it. |  |  |

7 DISCUSSION

In this paper, using a large dataset of public WhatsApp conversations from India, we perform the first large scale quantitative study to characterize fear speech. First, we manually annotated a large fear speech dataset. Analyzing the annotated dataset revealed certain peculiar aspects about the content of the fear speech as well as the users who post them. We observe that the fear speech messages are re-posted by more number of users to more groups as compared to non fear speech messages, primarily because the users who post such messages are centrally placed in the WhatsApp network. Fear speech messages clearly fit into a set of topics relating to aggression, crime, and, violence showcasing Muslims as criminals and using dehumanizing representations of them. We utilized state-of-the-art NLP models to develop classification models for fear speech detection and show that the best performing model can not be reliably used to classify fear speech automatically. Using Facebook ads survey, we observe that the fear speech users are more likely to believe and share fear speech related statements and significantly believe or support in anti-Muslim issues.

Given the prevalence of WhatsApp in India (and in the global south in general), the problem of fear speech and the advances in understanding its characteristics and prevalence are valuable. This is especially pertinent since WhatsApp is an end-to-end encrypted platform, where content moderation completely left out to the users. In our qualitative analysis of fear speech messages, we observed that many of them are based on factually inaccurate information meant to mislead the reader. Most users are either not equipped with the know-how to detect such inaccuracies or are not interested, hence getting more and more entrenched in dangerous beliefs about a community. We hope our paper will help begin a conversation on the importance of understanding and monitoring such dangerous speech.

One of the solutions to countering and reducing dangerous speech given the current end-to-end encrypted model on WhatsApp is to educate the users on the facts and encouraging with-in community discussion. Even though it is rare, we found some cases where the fear speech was countered with some positive speech. An example message – “The biggest challenge facing Indian Muslims at this time is how to prove themselves as patriots? From media to social media, Muslims are under siege, IT cell has waged a complete war against Muslims. … A very deep conspiracy is going on to break the country but we have to work hard to connect the country”. Such counter messages could be helpful in mitigating the spread of fear speech. Identifying users who post such messages and providing them incentives might be a good way forward.

Developing a client-side classifier, which can reside on a users device might be another option. More research needs to be done on both the accuracy of the model and the ability to compress it to fit on a smartphone. Another option is for platforms to make use of data from open social networks like Facebook to train fear speech models which can later be applied to closed platforms like WhatsApp.

Though we focused on fear speech against Muslims and on WhatApp in this paper, we can clearly see that the scope of this problem is not limited to Muslims nor to WhatApp. Our analysis also revealed instances of fear speech against other communities as well and as previous qualitative research suggests, the problem of fear speech might have a global context [36]. A quick Google search of our fear speech messages revealed the prevalence of the fear speech messages on other platforms, such as Facebook[30] and YouTube[31].

We hope that the dataset we release from our work will allow the community to build upon our findings and extend the quantitative research on fear speech broadly.

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30 e.g. https://www.facebook.com/The.Sanatana.Dharma/posts/2740274036014114
31 e.g. https://www.youtube.com/watch?v=ytU9jwNdkU
The focus of this paper was to introduce fear speech as an important and distinct topic to the Computational Social Science audience at the Web Conference, and encourage a quantitative analysis of fear speech. However, there are a lot of fundamental similarities in fear speech with prior work on hate speech. Efforts should be made to understand these similarities and build datasets and analyses that encompass such broader versions of dangerous speech.

Limitations. As with any empirical work, this study has its limitations. First, the data used is a convenience sample of public WhatsApp discussions on politics. Given that WhatsApp does not provide an API or tools to access the data, there is no way of knowing the representativeness of our dataset. This should be kept in mind while interpreting the results. However, we have been careful through out the paper stressing that this is a convenience sample, and that our objective was to focus on the problem of fear speech rather than the representativeness of our results on all of WhatsApp.

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