We further show one practical use of our framework by validating the feasibility of using social media to track the evolution of vaccination attitudes in real life. To address the impact of linguistic features such as sarcasm and irony commonly used in vaccine-related discourses, we integrate into the framework the recent posts of a user’s social network neighbours to help detect the user’s genuine attitude. Based on our annotated dataset from Twitter, the models instantiated from our framework can increase the performance of attitude extraction by up to 23% compared to state-of-the-art text-only models. Using this framework, we successfully validate the feasibility of using social media to track the evolution of vaccination attitudes in real life. We further show one practical use of our framework by validating the possibility to forecast a user’s vaccine hesitancy changes with information perceived from social media.

ABSTRACT

To address the vaccine hesitancy which impairs the efforts of the COVID-19 vaccination campaign, it is imperative to understand public vaccination attitudes and timely grasp their changes. In spite of reliability and trustworthiness, conventional attitude collection based on surveys is time-consuming and expensive, and cannot follow the fast evolution of vaccination attitudes. We leverage the textual posts on social media to extract and track users’ vaccination stances in near real time by proposing a deep learning framework. To address the impact of linguistic features such as sarcasm and irony commonly used in vaccine-related discourses, we integrate irony into the framework the recent posts of a user’s social network neighbours to help detect the user’s genuine attitude. Based on our annotated dataset from Twitter, the models instantiated from our framework can increase the performance of attitude extraction by up to 23% compared to state-of-the-art text-only models. Using this framework, we successfully validate the feasibility of using social media to track the evolution of vaccination attitudes in real life. We further show one practical use of our framework by validating the possibility to forecast a user’s vaccine hesitancy changes with information perceived from social media.

CCS CONCEPTS

• Computing methodologies → Information extraction.

KEYWORDS

social media, deep learning, graph neural networks, COVID-19, vaccination attitude

ACM Reference Format:
Ninghan Chen, Xihui Chen, Zhiqiang Zhong, and Jun Pang. 2022. "Double vaccinated, 5G boosted!": Learning Attitudes towards COVID-19 Vaccination from Social Media. In Proceedings of ACM Conference ‘Conference’17. ACM, New York, NY, USA, 11 pages. https://doi.org/XXXXXXXXXXXXXXX

1 INTRODUCTION

Vaccination is now unanimously accepted as an effective approach to combat the ongoing global COVID-19 pandemic, caused by the contagious coronavirus SARS-CoV-2 [34]. Despite the decreased efficacy against the infection of the recent variants, a high-level uptake of the currently available vaccines is still believed as key to restrain the numbers of severe diseases, deaths, and particularly hospitalisation, which is crucial for medical systems to remain operating as normal [4]. Regrettably, similar to the vaccines of other infectious diseases, not everyone is willing to be vaccinated [16]. The impact of vaccine hesitancy has been widely recognised and extensively studied in a number of countries for various groups of people, e.g., healthcare workers and immigrants. Many related factors and their influences are evaluated and compared, e.g., education, income and gender [10]. These scientific findings have provided policymakers with valuable references to design strategies to reduce vaccine hesitancy and fix the stagnant uptake ratios.

The success of these studies relies on the collection and accurate understanding of the public’s attitudes towards vaccination. Social surveys with well-defined questions, due to their reliability and trustworthiness, have been adopted as the dominant source of public opinions in the literature. However, as conducting surveys is expensive and time-consuming, they tend to fall behind the fast development of the COVID-19 pandemic [9], and thus fail in capturing the evolution of vaccine hesitancy. Continuous tracking of public vaccination attitudes can help healthcare bodies to identify the significant fluctuations to make a timely intervention or fast capture the public’s response to implemented policies. Moreover, it allows for analysing dynamic factors such as occasional social protests and misinformation propagation, in addition to the static ones like demographic profiles which rarely change in short periods.

In recent years, social media has attracted the attention of data analysts as an auxiliary data source to complement public health surveillance (PHS) in spite of its inherent bias, e.g., regarding population sampling [1, 9]. Due to social distancing and fear of the unknown, people spend more time than ever on social media. As social media posts have proved to encode posters’ subjective opinions [22, 24], in this paper, we aim to leverage the enormous daily posts during the COVID-19 pandemic to extract users’ vaccination attitudes and track their temporal changes.

We take advantage of the recent advances of deep learning in natural language processing (NLP), and propose a framework that can accurately classify a textual post according to the vaccination stance expressed by its originator. Our framework effectively addresses the challenge impairing existing NLP models’ performance, i.e., the linguistic features such as sarcasm and irony, which are
quite common in vaccination-related discourse. Consider the following example: “I wouldn’t do it for their vaccine, I’m waiting for the 6G”. The user expresses his/her support for vaccination by making fun of the conspiracy theory that chips are implanted with vaccine injection. After experimenting with the state-of-the-art text feature-based classification methods, we only get an accuracy of 0.65, which is apparently not reliable enough for trustworthy analysis. Recent studies revealed that a user’s vaccination attitudes correlate with those of their neighbours in social networks, e.g., friends and friends of friends. For example, online social network users with negative attitudes often have social relations with users of positive attitudes [24, 35]. Inspired by such studies, we integrate the recent posts of a user’s social network neighbours in our framework to help detect the user’s genuine attitude and reduce the impact of sarcasm.

To train and test models instantiated from our framework, we collect 9,135,393 tweets from Twitter generated by 69,936 users, and create the first annotated dataset of 18,246 tweets manually labelled with affective vaccination stances (e.g., positive and negative). In addition to the experimental evaluation, we draw the temporal evolution of vaccination attitudes extracted from our collected tweets. We cross-validate with published social studies and manually analyse the popular social events occurring around significant changes of vaccine hesitancy levels. All the validation results successfully illustrate the effectiveness of our framework, as well as the power of social media as a data source to grasp public vaccine hesitancy in practice in near real time.

Newsagents, governments, healthcare professionals and even anti-vaccine activists use social media to spread news, knowledge and suggestions to persuade or dissuade people from getting vaccinated [42]. To showcase the practical use of our post-based attitude learning framework, to the best of our knowledge, we are the first to demonstrate that the information that users perceive from social media can be used as predictors of their vaccine hesitancy changes.

Our contributions. Our contributions are as follows:

- We propose a framework to extract vaccination stances from textual social media posts. Our framework integrates recent posts of a user’s social network neighbours to help reduce the interference of linguistic features, e.g., sarcasm and irony.
- We design models instantiating our framework. Based on our annotated dataset from Twitter, the best model can increase the performance of attitude extraction by up to 23% compared to state-of-the-art text-only models.
- Using the model with the best performance, we track the evolution of vaccination attitudes. The utility of the extracted vaccination attitudes is further validated by the consistency with published statistics and explainable significant fluctuations of vaccine hesitancy in terms of social events such as wide propagation of misinformation and negative news.
- We show a practical use of our framework by validating the possibility to predict a user’s vaccination hesitancy changes with the information he/she perceives from social media.

Through this paper, we (re-)establish the power of social media as a complementary data source in public health surveillance in spite of its inherent biases. Specifically, when exploited properly, it can provide healthcare bodies with useful information to guide or support their decision-making processes.

2 RELATED WORK

Vaccine hesitancy is believed to be a major cause of stagnant vaccine coverage and contributor to vaccine program failure [16]. In spite of the lack of a unified definition, one widely accepted representation of vaccine hesitancy is a continuum, ranging from complete rejection of vaccines to varying degrees of scepticism [45]. In this section, we concentrate on the vaccine hesitancy studies after the onset of the COVID-19 pandemic. A considerable amount of literature has been published investigating the state of vaccine hesitancy and the influential factors in different regions [25, 41] for specific groups of people such as healthcare employees [8, 21], immigrants [3] and college students [5]. Although surveys are still the most adopted method to collect sampled populations’ attitudes or stances toward vaccination [2], some recent works leverage social media as a new dimension [22, 24]. Compared to self-reporting questionnaires, social media data are cost-effective to access, and more importantly, allow analysis over large populations which was not previously feasible [1, 9, 24].

The methods extracting vaccination attitudes from social media fall into two categories: community-based and post-based. Cosnard et al. [13] found pro- and anti-vaccine users naturally cluster into communities and calculated community partitions of various communication graphs to infer users’ vaccination stances. Johnson et al. [24] made use of the topics of fan pages (similar to discussion groups) on Facebook to approximate users’ attitudes, and analysed the communities formed by 100 million users across the world in terms of their vaccination attitudes. Post-based methods benefit from the various types of information encoded in social media posts such as texts, labels and pictures. Gunaratne et al. [22] relied on the hashtags in tweets to approximate the vaccination attitudes in tweets. Sentiment analysis, as part of natural language processing (NLP), aims to derive the subjective opinions expressed in texts. The introduction of deep learning leads to more powerful models that can process posts at the sentence or paragraph levels such as word2vec [33] and BERT [15]. The sentiments extracted from texts have been used as references to study vaccine hesitancy [20]. For instance, Gbashi et al. [20] detected the opinions of media towards vaccines in Africa through Twitter and Google news.

Discussion. The community-based methods cannot capture the fast development of public vaccination attitudes due to the relatively stable connections between users. Moreover, community memberships are effective for analysis on the level of populations but fail to accurately derive individual users’ attitudes. The post-based methods in previous studies are not specifically designed and trained for COVID-19 vaccines. As a result, they cannot capture the special linguistic characteristics of the online discourses during the COVID-19 pandemic. This is partially because of the lack of social media posts which are related to COVID-19 vaccines and annotated with vaccination stances. In this paper, we propose a framework that can not only benefit from state-of-the-art post-based methods, but also deal with the interference of linguistic features such as sarcasm and irony in discourses related to COVID-19 vaccination. We
also create the first annotated dataset of tweets which can facilitate developing future models on subjective opinion extraction.

3 EXTRACTING VACCINATION ATTITUDES FROM SOCIAL MEDIA POSTS

3.1 Problem definition

Extracting the vaccination stance of a social media post can be technically formulated as a natural language processing (NLP) task [30], i.e., classifying texts according to given class labels. In this paper, we focus on the affective stance towards COVID-19 vaccination. Thus the set of labels is \( \mathcal{L} = \{ \text{NE, PO, NG} \} \) where NE, PO and NG correspond to neutral, positive and negative, respectively. The basic idea of text classification in NLP is first to calculate a representation of the given text which summarises its linguistic features and then output the most likely class label. Classification methods differ from each other in terms of the formats of text representation and the mapping from representations to class labels. Text classification confronts the challenge that the attitude or emotion expressed by the same words varies according to the context. For instance, the figurative usage of symptom words can fool the keyword-based classification methods and significantly deteriorate the precision of health mention classification [7]. Sentiments of the short texts with symptom words are thus introduced as auxiliary information to deal with this figurative interference.

As discussed previously, we notice that during the COVID-19 pandemic, Twitter users tend to use sarcastic or ironic expressions to describe their disagreements with those with different vaccination stances. Inspired by previous works such as [7], given a post, we aim to benefit from the originator’s social relations as well as their past posts to help reduce or eliminate the interference of sarcasm and irony.

We use \( \mathcal{G} = (\mathcal{V}, \mathcal{E}) \) to represent the social graph recording the social relations between users where \( \mathcal{V} \) is the set of nodes and \( \mathcal{E} \subset \mathcal{V} \times \mathcal{V} \) is the set of edges between nodes. A node \( v \in \mathcal{V} \) corresponds to a social media user and an edge \((v, v')\) indicates the existence of a relationship between two users \( v \) and \( v' \). Note that we ignore the direction of relationships in this paper to take into account all the neighbours of a user, e.g., both followers and followees on Twitter. Thus, \((v, v') \in \mathcal{E} \) implies \((v', v) \in \mathcal{E} \). We abuse the terms user and node in the following discussion when it is clear from the context. Let \( N^k_v \) be the set of neighbours of node \( v \) within \( k \) hops, i.e., \( \{v | d_{\mathcal{G}}(v, v_i) \leq k \} \) where \( d_{\mathcal{G}}(v, v_i) \) is the shortest distance between \( v \) and \( v_i \) in the graph \( \mathcal{G} \). Note that node \( v_i \) is also in \( N^k_{v_i} \) as \( d_{\mathcal{G}}(v_i, v_i) = 0 \). We use \( x^t_i \) to denote the textual message posted by user \( v_i \) at time \( t \). We use \( M^<_{\mathcal{N}^k_v} \) to denote the list of posts originated by user \( v_i \) before time \( t \) chronologically ordered by their post time, and \( M^\leq_{\mathcal{N}^k_v} \) to represent the set of post lists of the neighbours of user \( v_i \) within \( k \) hops.

Our COVID-19 vaccination attitude classification problem can be defined as calculating the probability distribution of all labels in \( \mathcal{L} \). The final vaccination stance of \( x^t_i \), i.e., \( f(x^t_i) \), is determined by the label with the largest probability. Formally, we have

\[
\hat{f}(x^t_i) = \arg\max_{\text{stance} \in \mathcal{L}} \Pr(\text{stance} | x^t_i, \mathcal{G}, M^\leq_{\mathcal{N}^k_v}).
\]

Figure 1: An illustration of our attitude classification framework and model.

3.2 A vaccination attitude learning framework

To solve the classification problem formulated previously, we propose a framework which takes advantage of the recent success of adopting deep learning in NLP and graph analysis such as text embedding and graph neural networks (GNNs).

Figure 1 depicts an overview of our framework by labelling its three main components in different background colours: i) a text-level information embedding module, ii) a GNN-enhanced module, and iii) a classification module. The first module is used to learn the linguistic representation of the targeted post while the second module summarises the linguistic features of the recent messages posted by the user’s neighbours. We concatenate the outputs of these two modules as the input of the classification module. GNN [27] has shown its advantage in transforming graph information, including structures and attributes of nodes and edges in both academia and industry. Intuitively, it employs a message passing scheme to integrate the information of a node’s neighbourhood as the representation of the node. The calculated embedding is then used for various downstream applications such as node classification and link prediction. Variants of GNN differ from each other in terms of the implementation of their message passing schemes.

Our framework can be instantiated by assembling various methods that can achieve the corresponding tasks of the modules. In the following, we present how we implement every module of the framework and justify our choices.

3.3 Our model

Text-level information embedding. In order to mine meaningful information from a limited number of annotated posts, recent solutions leverage pre-trained NLP transformers to calculate the embedding for short texts [31]. NLP transformers have been empirically evaluated in [46] where RoBERTa [32] is shown to outperform the competing models. Due to its high effectiveness, we adopt RoBERTa to learn text representations in our model. The model
takes a textual post, e.g., \( x_i \), as input, and outputs a sentiment-oriented representation vector \( z_i^{\text{text}} \in \mathbb{R}^d \) where \( d \) is the pre-defined dimension of the vector. RoBERTa will be fine-tuned with the posts in the training set.

**GNN-enhanced module.** Given the target post \( x_i \), we utilise this module to capture the linguistic features of the recent messages posted by \( v_i \)’s friends within \( k \) hops before \( t \). The definition of “recent” is flexible and depends on application scenarios. In this paper, we select the last \( \lambda \) posts before \( t \) as a user’s recent tweets. Its output will be subsequently used as complementary contextual information to further ameliorate classification performance. Therefore, the input of this module consists of the social network \( G \) and the historical messages of user \( v_i \)’s \( k \)-hop neighbours, i.e., \( M_i^{k\ell} \).

Note that the post originator’s recent messages are also considered as \( v_i \) is included in \( N_i^k \). The output will be a text-level embedding vector that can be intuitively interpreted as a summary of useful features of friends’ recent discourse.

We take two successive steps to calculate the output text-level representation vector \( z_{i,t} \). We first integrate the recent posts of each user in \( v_i \)’s \( k \)-hop neighbourhood as a summary of his/her vaccination discourse. In the second step, we propose a new GNN-based model named by H2GAT to aggregate the discourse of all \( v_i \)’s neighbours into the social text encoding vector.

**STEP 1: Text-level encoding.** For each user \( v_j \in N_i^k \), we use his/her last \( \lambda \) posts in \( M_j^{\ell t} \), denoted by the list \( \{x_j^1, x_j^2, ..., x_j^\lambda\} \) where \( t_m = \{1 \leq m \leq \lambda \} \) is the time stamp of \( v_j \)’s last \( m \)-th post. We apply the pre-trained RoBERTa model and then obtain the corresponding list of text-level representations, i.e., \( \{z_{j,1}^{\text{text}}, z_{j,2}^{\text{text}}, ..., z_{j,\lambda}^{\text{text}}\} \). There are many ways to integrate \( v_j \)’s past text-level representations while distinguishing their various temporal importance, e.g., Hawkes [23] and GRU [12]. In our implementation, we adopt the dynamic-aware *position encoding* by assigning a fixed importance factor to each past post according to its position in the list. This method is simple but more effective than other competing ones in our experiments (as shown in Section 5). Formally, the integrated text-level representations of user \( v_j \) is calculated as follows:

\[
z_{j,t}^{\text{hist}} = \sum_{m=1}^{\lambda} \alpha_m \cdot z_{j,m}^{\text{text}}
\]

where \( \alpha_m \) is trainable and describes the positional relation between the past posts. Note that \( k \) and \( \lambda \) are predefined hyper-parameters that should be tuned manually.

**STEP 2: H2GAT.** It is pointed out that the *heterophily* phenomenon widely exists among online social network users [39]. This phenomenon also exists in vaccination-related discourses as the attitudes and linguistic features can be significantly different between users. Considering the heterophily of vaccination discussion in a user’s neighbourhood, we adopt and extend a recent GNN-based method called H2GCN [47]. The same as other GNNs, it also has multiple layers, the \( \ell \)-th of which can be formulated as follows:

\[
H_\ell^i = \text{Combine}((\text{Aggregate}(H_{j,\ell-1}^j : j \in \tilde{N}_i^{k^\ell}) : k^\ell \in \{1, ..., k\}))
\]

where \( \tilde{N}_i^{k^\ell} \) represents node \( v_i \)’s \( k^\ell \)-order neighbours, i.e., nodes that have an exact distance of \( k^\ell \) from \( v_i \) in \( G \). Formally, \( \tilde{N}_i^{k^\ell} = \{v_j \mid d_G(v_j, v_i) = k^\ell\} \). Note the difference of \( \tilde{N}_i^{k^\ell} \) from \( N_i^{k^\ell} \). As \( G \) is connected, when \( k^\ell > 0 \), we have \( \tilde{N}_i^{k^\ell} \subset N_i^{k^\ell} \). The initial \( H_0^i \) for each \( v_j \in \mathcal{V} \) is set to \( z_{j,t}^{\text{hist}} \).

Note that different from [47] which adopts the Aggregate function of GCN [27], we use GAT [43] for better performance. The output representation of \( v_i \), denoted by \( z_{i,t}^{\text{social}} \), is calculated by combining node representations of all layers:

\[
z_{i,t}^{\text{social}} = \text{Combine}((H_0^i, H_1^i, ..., H_L^i)).
\]

Many ways exist to implement the function Combine. We adopt the one in H2GCN [47] in our model which outputs the concatenation of all inputs.

By concatenating \( z_{i,t}^{\text{social}} \) and \( z_{i,t}^{\text{text}} \), we obtain the text-level representation vector for classification. Formally,

\[
z_{i,t} = z_{i,t}^{\text{social}} \| z_{i,t}^{\text{text}}.
\]

**Attitude classification.** We implement a simple two-layer structure to conduct the classification. Note the output vector has a length of \( |\mathcal{L}| \). Recall \( \mathcal{L} \) is the set of class labels. The first layer applies the ReLU function to each element in \( z_{i,t} \) and at the second layer, we use a linear regression where \( W \in \mathbb{R}^{2d|\mathcal{L}|} \) and \( b \in \mathbb{R}^{|\mathcal{L}|} \) is the bias vector. The softmax function is applied to calculate the probability distribution over the class labels. Formally, the distribution \( p \) is calculated as follows:

\[
p = \text{softmax}(\text{ReLU}(z_{i,t}) \cdot W + b).
\]

The class label with the largest probability will be chosen as the output. We use CrossEntropyLoss as the objective function to train the entire model.

### 4 DATA CURATION

To train and evaluate our vaccination attitude learning framework, we collect a dataset from Twitter focusing on four adjacent Western European countries: Germany, France, Luxembourg and Belgium. Reasons to select these countries include their importance to European economy and their similar and almost synchronous pandemic management policies. They can also well represent the first group of countries receiving and administering COVID-19 vaccines. Due to the lack of publicly available data with vaccination stances, we create the first public set of annotated tweets for training and testing our framework. The statistics about our dataset are summarised in Table 1. This dataset and our annotation are publicly available.\(^1\)

\(^1\)The download link is hidden due to the double-blind review policy.

### 4.1 Data collection and preprocessing

Our dataset consists of two types of data: i) a social network composed of active Twitter users, and ii) the tweets of selected users related to COVID-19 vaccine or vaccination. By ‘active users’, we mean users that are active in vaccination-related discussion and frequently interact with others.

**Step 1. Social graph construction.** We start with identifying the Twitter users in our targeted region who actively participated in vaccine-related discourse. Instead of directly searching tweets by keywords, we refer to a publicly available dataset which contains the IDs of COVID-19 related tweets [11]. We extract the tweet IDs spanning between January 22, 2020 and March 15, 2021 covering...
the beginning of the vaccination campaign. Through these IDs, we download the corresponding tweets. Each downloaded tweet is associated with meta-information which includes the location of the originator, either self-provided by the originator or attached by the device’s positioning services such as GPS. Due to the ambiguity of the self-reported locations, we use the geocoding APIs, Geopy and ArcGIS Geocoding to regularise their formats. For example, a user input location Moselle is transformed to a preciser and machine-parsable location: Molselle, Lorraine, France. Based on the regularised locations, we filter the downloaded tweets and remove those posted by users out of the region. In total, we obtain 990,448 tweets from 767,583 users.

To find the users with frequent interaction with other Twitter users, we construct a re-tweeting weighted graph. An edge is created between two users if one user retweeted a tweet from the other user or mentioned him/her. The edge weight is assigned as the number of mentions or retweets between them. We remove all edges with weights smaller than two and calculate the largest weakly connected component of the graph which consists of 72,960 active users. As retweeting or mentioning a user does not mean these two users have a following relationship, we crawl the remaining users’ followers, with which a graph is constructed with the remaining users and the relationships between them as edges. In the end, we take the largest weakly connected component of the resulted graph as the final social graph. This graph consists of 69,936 nodes and 8,909,985 edges. On average, each user has 127.4 followers. This indicates our selected users are sufficiently active on Twitter.

Step 2. Vaccine-related tweet collection. In this step, we crawl the tweets originated or retweeted by the users in the social graph. Note that we are only interested in the tweets related to COVID-19 vaccination. We use a list of keywords to filter out the irrelevant ones. The keywords should be general enough to cover tweets in German, French and English. With our observation and several trials, we select the keywords containing the following strings: ‘vax’, ‘vaccin’, ‘covid19’, ‘impfstoff’, ‘vaccine’, ‘vacuna’ and ‘impfung’. We use the Twitter Academic Research API to download tweets. Due to the limitations of the API, each request can only download a maximum of 500 tweets. To be efficient and ensure the coverage ratio, we create a download request for every user in each month. In total, we collect 1,626,472 tweets, and each user has about 130 tweets on average. We clean the downloaded tweets by removing mentions of other users with ‘@’, quoted hyperlinks and ‘RT’.

4.2 Data annotation
According to the best of our knowledge, no datasets of social media posts are publicly available with users’ COVID-19 vaccination attitudes annotated. As a result, we select a subset of our downloaded tweets and manually attach them with attitude labels. In this paper, we focus on users’ affective stances towards COVID-19 vaccination which are positive, negative and neutral. Table 2 lists examples of the attitude labels. After a closer check of the tweets, we notice a relatively large number of tweets in which users express their dissatisfaction or complaints about governments’ COVID-19 management policies but possess positive attitudes towards vaccination. Take the last row in Table 2 for an example. It contains a few negative words such as ‘bad’, ‘criminal’ and ‘waste’ but the originator explicitly expresses his/her support for vaccination. As such tweets deliver a negative emotion, if we do not separate them from those with negative vaccination attitudes, NLP models will be confused and their classification accuracy will be deteriorated. Therefore, we add a label PD indicating ‘positive but dissatisfied with government management’. Then the set of labels L, used in the rest of the paper, consists of four labels, i.e., {PD, PO, NG, NE, PD}.

We select tweets to be annotated with the purpose to cover all the users in our dataset. We order our downloaded tweets in a list according to their numbers of times being re-tweeted in descending order. We then iteratively remove the most transmitted tweet from the list and put it into the list of selected tweets until every user in our dataset originally posted or retweeted at least one selected message. After this step, we select 18,246 tweets originated from 4,157 users.

As our tweets are multilingual, we hire 10 bachelor students who can speak at least two of the three most used languages (i.e., German, French and English). One author of this paper acts as the coordinator and trains all the hired annotators by explaining the semantics of all labels with examples. To ensure all annotators hold the same understanding of all labels, they are asked to annotate 200 tweets. The coordinator checks their annotation and communicates to them with extra explanation when necessary. We conduct three rounds to make sure each tweet’s label is double-validated. In the first round, an annotator annotates all the selected tweets. In the second round, each of the rest 9 annotators is assigned randomly 2,000 tweets and validates the annotation. In the last round, the

| Table 1: Dataset statistics. |
|-------------------------------|
| Social network               | #node | France | 35,081 |
|                              |       | Germany | 16,304 |
|                              |       | Belgium | 15,647 |
|                              |       | Luxembourg | 2,904 |
|                              | #edge | 69,936 |
|                              | avg. degree | 8,909,985 |
| Tweets                       | #tweet | France | 5,925,354 |
|                              |       | Germany | 2,669,875 |
|                              |       | Belgium | 530,885 |
|                              |       | Luxembourg | 9,279 |
|                              | #tweet | 9,135,393 |
|                              | tweet/user | 130.62 |
| Annotated tweets             | #tweet | 18,246 |
|                              | ruser | 4,157 |

| Table 2: Annotation labels and examples. |
|------------------------------------------|
| Label           | Examples (translated to English)                  |
| positive        | We have a new weapon against the virus; the vaccine, Hold together, again. |
| negative        | This nurse gets covid19 vaccine; then she talks to media how great it is; then passes out; watch! |
| neutral         | How safe is the Covid19 vaccine for people with diabetes? |
| positive but dissatisfied with government management | It’s bad enough for individuals to refuse #COVID19 #vacines for themselves. But forcing a mass vax site to shut down, knowing it means vaccines may go to waste, is criminal. Call it pandemicied. |
Annotator agreement. We leverage three widely accepted measures to evaluate the inter-annotator reliability for each label: Average Observed Agreement (AOA) [19], Fleiss’ kappa [19], and Krippendorff’s Alpha [28]. The values of all the three measurements range from 0 to 1, where 0 indicates complete disagreement and 1 indicates absolute agreement. Table 3 summarises the inter-annotator agreement for each annotation label. We can see that for labels PO, NG and NE, all the three measurements produce scores larger than 0.73, indicating an outstanding agreement level. The annotators’ agreement on PD falls drastically compared to other labels, but still remains moderate according to the ranking criteria of the Fleiss’ Kappa measurement. This can be explained by our difficulties during annotation dealing with the special linguistic features of PD tweets, i.e., frequently used negative terms or sarcastic expression.

5 EXPERIMENTAL EVALUATION

Evaluation setup. We set up an evaluation pipeline following the approach for traditional supervised classification [34]. Specifically, we split labelled tweets into training (80%), validation (10%) and testing (10%) sets. The models are optimised with the training set, and the validation set is used to tune hyper-parameters. The model performance is evaluated on the testing set.

Hyperparameter settings. We train our model for 400 epochs and use Adam [26] for optimisation with the learning rate of $10^{-5}$ and weight decay of $5 \times 10^{-4}$. For the text encoder, i.e., RoBERTa, we adopt the implementation XLM-RoBERTa [38] and follow their default settings where the maximum string length, i.e., parameter $d$, is 128. For our GNN-enhanced module, we set the embedding dimension as 64. The neighbourhood order $k$ which is also the number of layers and the number of historical tweets $\lambda$ are important to ensure representation quality. Therefore, we conduct an empirical study to analyse the influence of these two key hyper-parameters to ensure the final performance. In Figure 3, we present the classification accuracy with different values of $k$ (on the left) and $\lambda$ (on the right). We observe that these two hyper-parameters indeed significantly influence classification accuracy. Our model arrives at the best performance with $k = 2$ and $\lambda = 3$.

Experimental results. We compare our model with other possible implementations of our proposed vaccination attitude learning framework. In order to distinguish these models, we name them with two parts concatenated with ‘+’. The first part tells the adopted GNN model while the second part gives the method handling the temporal importance of past tweets. As all models use RoBERTa for text encoding, we do not explicitly put it in the model names. We present their performances in Table 4.

We have four major observations that justify the effectiveness of our implementation. First, the consideration of friends’ vaccination discourse increases the performance. The text-only classification model with RoBERTa only has an average accuracy of 0.65 while the other models, which are implemented with the GNN-enhanced module, achieve at least an accuracy above 0.70. Second, the vaccination discourse between friends on Twitter is actually heterophily and the choice of heterophily-aware GNN models, i.e., H2GCN and our H2GAT, can further significantly improve the performance. The next four models below RoBERTa in Table 4 have the same settings except for the GNN methods. Both the application of H2GCN and our H2GAT achieve an increase of about 0.04 compared to the models with GCN [27] and GAT [43]. Third, the consideration of the temporal importance of past tweets leads to another up to 0.06 improvement. We consider four methods to combine a user’s last $\lambda$ tweets: MEAN, GRU, Hawkes and PE (short for positioning encoding). The method denoted by MEAN simply averages the text-level encodings. The positioning encoding method adopted in our model generates the best performance. Last, our extended H2GAT model outperforms the original H2GCN. Our implementation, i.e., H2GAT+PE, finally improves the text-only RoBERTa model by 23% in terms of accuracy.

Empirical complexity analysis. As the RoBERTa model is pre-trained, the models instantiated from our framework have the same complexity as the adopted GNN models. In our experiments, we
conduct the training on a server with Xeon E5 CPU and Tesla V100 GPU. On average, the training time for RoBERTa is about 115 seconds for an epoch while 52.5 seconds are needed for an epoch in training the GNN-enhanced module and the classification module. What is more important is the running time of the models when processing a tweet. This will determine the practical utility of our framework in tracking public vaccination attitude in real time. We run four parallel instances of our model H2GAT+PE on the server. On average, it takes 24.68 seconds for every 1,000 tweets, which means more than 3.5 million can be processed a day. For the regions we target at, we collect in total 9 million vaccination-related tweets over two years. This implies our model is sufficiently efficient for processing posts on a daily basis.

**Cross-validation.** In addition to experimental evaluation, we also make use of published social studies to cross-validate our model’s effectiveness. Lazarus et al. conducted a survey in June 2020, and estimated that the vaccine acceptance rates in France and Germany are 58.9% and 64.5%, respectively [29]. After applying our model to classify the tweets in the same period, we find the percentages of tweets with positive vaccination attitudes of these two countries are 42.27% and 53.12%, which are similar and retain the relative difference between the two countries. This implies that posts on Twitter can be used as a reference to fast grasp the vaccine hesitancy levels when surveys are not available.

**Vaccine hesitancy tracking and manual analysis.** We draw the temporal evolution of the percentage of tweets for each selected label in Figure 4 on a daily basis starting from November 8, 2020. Based on previous research reporting that the content of tweets is highly correlated with real-world situations [40], we make a hypothesis that real-world events may contribute to the fluctuating proportion of tweets with different vaccination stances. In vaccine hesitancy monitoring, special attention should be paid to the fluctuations of negative attitudes. We take three time points that correspond to turning points of the curve of label NE as examples and discuss the potential causes. Among them, two correspond to apex points where negative tweets reach local maximum percentages and one corresponds to a base point with local minimum negative tweets. We first plot word clouds in Figure 5 to identify the most frequently used keywords in the week around the selected points. Then we search these keywords on the Internet to identify the events that may contribute to the changes.

The first apex occurred around January 16, 2021. We notice that this surge of negative tweets attributes to the propagation of a large volume of misinformation. Take the two most dominant pieces of misinformation as examples. One said that on January 14, the Norwegian Medicines Agency reported that a total of 29 people had suffered side effects, 13 of which were fatal. The other was about the death of an Indian healthcare worker after receiving COVID-19 vaccines. The second peak happened around February 15, 2021. One piece of negative news was reported that AstraZeneca vaccines were stopped from administration after many health workers of Morlaix hospital in France suffered from side effects. This news subsequently led to anti-vaccination discussions. The base point occurred between the two peaks around February 3, 2021. From Figure 5(c), we find the dominant positive news that Russia started to offer other countries such as Pakistan with its vaccines.

![Figure 4: Temporal distribution of tweets with different vaccination attitude labels.](image)

![Figure 5: Word clouds of tweets around selected points.](image)

**Figure 5: Word clouds of tweets around selected points.** From the above discussion, we can see our model can enable the use of social media data to track on a daily basis the changes of vaccination attitudes, and capture the impact of social events on public vaccine hesitancy. This may finally help the governments identify the right time to take intervention actions.

### 6 USE CASE: PREDICTING VACCINATION HESITANCY CHANGES

In this section, we illustrate a use of our vaccination attitude learning framework. Specifically, we analyse the role of the vaccination information widely spread across Twitter in affecting users’ attitudes towards vaccination. Considering the comprehensiveness of vaccination discourses, we classify the most popular vaccination-related tweets into themes that may correlate with vaccine hesitancy. Based on users’ perceived information in these themes, we succeed in forecasting their vaccination attitude changes with classic machine learning models.

#### 6.1 Period selection and theme labelling

The participation of vaccination discourses fluctuates over time along with the occurrence of social events related to COVID-19 vaccines. We select two time periods after the start of COVID-19 vaccination campaign, in which the volume of tweets experiences significant surges compared to adjacent periods. The first period lasts for 25 days spanning from December 27, 2020 to January 20, 2021 while the second period lasts for 15 days between January 25 and February 8, 2021. These two periods involve 161,611 original tweets posted in total among which 25,449 are retweeted at least once. The total number of times of being retweeted adds up to 242,129. We encounter two challenges to continue our analysis of the impact made by diffused information: the comprehensiveness and large volume of propagated tweets. Due to the huge volume of tweets propagated over Twitter, it is not plausible to consider all of them. Previous studies show that tweets’ influence follows the power-law distribution and 80% of the impacts come from 20% of the most widely spread tweets [18]. Inspired by this result, we leverage the top 25% most widely propagated tweets in every
we consider the user’s attitude
we only use the texts users upload as valid posts encoding users'
Table 5: Model performances for attitude change prediction.

| Model          | Precision | Recall | F1 | Accuracy |
|----------------|-----------|--------|----|----------|
| SVM            | 0.7374    | 0.7382 | 0.7445 | 0.7477 |
| Naive Bayes    | 0.6468    | 0.6559 | 0.6427 | 0.6658 |
| Random Forest  | 0.6811    | 0.6838 | 0.6795 | 0.6958 |
| XGBoost        | 0.7232    | 0.7229 | 0.7198 | 0.7342 |
| GBDT           | 0.7533    | 0.7516 | 0.7498 | 0.7603 |

period to approximately represent the themes expressed in the
diffused information. In total, we select 501 original tweets that
are retweeted 78,891 times from 72.16% of the users. To deal with
the comprehensiveness, with a careful examination of the selected
tweets, we categorise them into themes that are considered to
be responsible for the changes of vaccination attitudes. We refer
to previous studies [6, 14], especially the Parent Attitudes about
Childhood Vaccines (PACV) survey [36] and the WHO Vaccine
Hesitancy Matrix [37], and identify 11 themes that are relevant
and can cover the propagated tweets (see Table 6 in Appendix for
explanation and examples). We ask two of the 10 hired annotators
to manually annotate the selected tweets with their corresponding
themes. The Cohen’s Kappa coefficient \(k = 0.82\) implies a high rate
of agreement between them.

6.2 Predictability of vaccine hesitancy changes
Handling retweets and quotations. In addition to original posts,
retweets and quotations also take up a large proportion of a user’s
historical posts. For quotations, a user added some comments which
may express opposite opinions to that of the quoted one. Therefore,
we only use the texts users upload as valid posts encoding users’
vaccination stances. Although retweets cannot fully represent a
user’s own opinion, the behaviour of retweeting itself indicates
some sort of agreement with the ideas expressed in the message
retweeted [17]. Based on this idea, we take retweets into account
when calculating an individual user’s vaccine hesitancy. The same
approach is also adopted in the vaccination attitude tracking dis-
cussed in the previous section.

Quantifying individual vaccine hesitancy. We measure the vac-
cine hesitancy of an individual user according to the tweets posted
or retweeted by the user in a time interval. Formally, it is calculated as:

\[
N_p(v) - N_n(v) \over N_p(v) + N_n(v)
\]

where \(N_p(v)\) denotes the number of posts with positive vaccination attitudes of user \(v\) during the selected interval, and \(N_n(v)\) is the corresponding number of tweets with negative attitudes. Considering our purpose being idea validation, we do not distinguish the various significance of original posts and retweets.

For each selected period, we use the tweets posted 14 days before
and after the period to evaluate individual users’ hesitancy levels
and see how they change. In order to ensure the reliability, we only
consider the users who posted or retweeted at least 3 tweets. If a
user’s vaccine hesitancy experiences a change smaller than 0.05,
we consider the user’s attitude unchanged, otherwise, increased or
decreased depending on the change direction.

Modelling perceived information. A Twitter user perceives in-
formation from the tweets retweeted or originally posted by his/her
direct friends. As our focus is the information widely diffused on
Twitter, we use a vector \(I_u = (c_1, c_2, \ldots, c_m)\) to approximately rep-
resent a user \(u\)’s perceived information where \(c_i\) is the number of
popular tweets a user receives from followers in \(i\)-th theme. As we
have 11 themes, \(m = 11\) in our analysis.

Model evaluation. We make use of various standard machine
learning methods to predict the change of a user’s vaccination
attitudes with the input of \(I_u\). The methods consist of SVM with
rbf kernel (\(C = 1, \gamma = 0.1\)), Naive Bayes (\(\alpha = 1\)), Random Forest
(100 trees with maximum tree depth of 5), XGBoost (100 trees with
maximum tree depth of 4) and GBDT (100 trees with maximum tree
depth of 5). Table 5 shows the performance of these methods. All
numbers are averaged over 5 training sessions. We can see all the
methods can achieve reasonably good prediction performance and
GBDT outperforms the rest models with an accuracy of 0.76. When
we consider additional factors such as users’ vaccine hesitancy
levels before the periods, the accuracy can be improved to 0.86.

Discussion. These results show that we can make accurate pre-
dictions with users’ perceived popular information. Since we have
empirically illustrated the plausibility to use social media posts to
track public vaccination attitudes, the results imply that the diffused
information on social media like Twitter could be used as indicators
to forecast the changes of vaccine hesitancy levels. As repeated
many times, although such predictions cannot achieve the same
level of trust as social surveys, they provide decision-makers with
a method to quickly understand and get prepared for the potential
damage of certain misinformation or compare different vaccine
hesitancy intervention strategies over social media.

7 CONCLUSION AND DISCUSSION
In this paper, we proposed a deep learning framework to learn
vaccination attitudes from social media textual posts. Although
vaccination attitudes extracted from social media cannot be as ac-
curate and reliable as conventional social surveys, our framework
allows for continuously tracking the fast development of public
vaccination attitudes and capturing the changes that deserve spe-
cific attention in time. By leveraging friends’ vaccination discourse
classification as contextual information, our model successfully reduces the interfer-
ence of linguistic features such as sarcasm and irony. Our model
instantiated from the framework improves the state-of-the-art text-
only method by up to 23% in terms of accuracy according to our
manually annotated dataset. With cross-validation with published
statistics and manually analysis, we further validated the effective-
ness of the model to capture public vaccine hesitancy in real life.
After identifying 11 themes from widely diffused information on
Twitter, with the help of our model, we validated the predictability
of users’ vaccine hesitancy changes by the information they per-
ceived from social media. This showed a potential use of our model
in practice. Through this paper, we established again the power
of social media data in supplementing public health surveillance,
especially in combating infectious virus like COVID-19.

Limitations and future work. We have three main limitations
to address in future. First, in our work we have primarily focused
on Twitter which potentially induces bias in our data and analysis.
Thus, it is important to extend our work to other social media plat-
forms such as Facebook and Instagram, and cross-validate our re-
sults. Second, we only analysed users’ affective vaccination stances
(i.e., positive, negative and neutral), which can only be used as an
indicator of users’ intention of getting vaccinated. It will be interesting to look deeper into users’ tweets for a longer time and identify underlying determinants that lead to vaccination acceptance. Third, we associated only the top 25% most widely spread tweets as representatives to extract the themes of diffused information partly limited by manual annotation. Some information in certain themes may be missed. As an interesting future work, we will develop effective NLP models to learn different tweet themes automatically.

Ethical considerations. This work is based completely on public data and does not contain private information of individuals. Our dataset is built in accordance with the FAIR data principles [44] and Twitter Developer Agreement and Policy and related policies. Our release of the dataset is also compliant with General Data Protection Regulation (GDPR). To conclude, we have no ethical violation in the collection and interpretation of data in our study.

REFERENCES

[1] Allison E Aiello, Audrey Renson, and Paul N Zivich. 2020. Social media- and internet-based disease surveillance for public health. Annual Review of Public Health 41, 1 (2020), 118–131.

[2] Rasmieh Al-Am, Della Maneeze, Bronwyn Everett, Jed Montayre, Amy R Vilzaros, Entisar Dwekat, and Yenna Salammon. 2021. COVID-19 vaccination intention in the first year of the pandemic: A systematic review. Clinical Nursing Research 31, 1–2 (2021), 62–86.

[3] Majid Alabdulla, Shuja Mohd Reagag, Abdullah Al-Khal, Marwa Elzain, and Roland M Jones. 2021. COVID-19 vaccine hesitancy and attitudes in Qatar: A national cross-sectional survey of a migrant-majority population. Influenza and Other Respiratory Viruses 15, 3 (2021), 361–370.

[4] Nick Andrews, Julia Stowe, Freja Kirelsbom, Samuel Tofta, Ruchira Sachdeva, Charlotte Gower, Mary Ramsay, and Jamie Lopez Berna. 2022. Effectiveness of COVID-19 booster vaccines against COVID-19 related symptoms, hospitalisation and death in England. Nature Medicine (2022).

[5] Serena Barella, Tiziana Nanica, Federica Delfiarella, Guendalaina Graffigna, and Rosario Caruso. 2020. Vaccine hesitancy among university students in Italy during the COVID-19 pandemic. European Journal of Epidemiology 35, 8 (2020), 781–783.

[6] Aida Bianco, Valentina Mascaro, Rossella Zucco, and Maria Pavia. 2019. Parent perspectives on childhood vaccination: How to deal with vaccine hesitancy and refusal? Vaccine 37, 7 (2019), 984–990.

[7] Rhys Biddle, Aditya Joshi, Shaowu Liu, Cécile Paris, and Guandong Xu. 2020. BERTpretraining of deep bidirectional transformers for language understanding. In Proc. 2020 International Conference on Learning Representations (ICLR). OpenReview.net.

[8] Nirbachita Biswas, Toheeb Mustapha, Jagdish Khubchandani, and James H Price. 2021. Associations between exposure to and expression of negative opinions about human papillomavirus vaccines on social media: An observational study. Journal of Medical Internet Research 17, 6 (2015), e144.

[9] Joseph L Fleiss, Bruce Levin, and Myunghee Cho Paik. 2013. Statistical methods for rates and proportions. John Wiley & Sons.

[10] Fidelia Cascini, Ana Pantovic, Yazan Al-Ajlouni, Giovanna Failla, and Walter Ricciardi. 2021. Attitudes, acceptance and hesitancy among the general population to COVID-19 vaccination in the United States: A rapid national assessment. Journal of Community Health 46, 2 (2021), 270–277.

[11] Emily Chen, Kristina Lerman, and Emilio Ferrara. 2020. Tracking social media and Twitter Developer Agreement and Policy and related policies. Our release of the dataset is also compliant with General Data Protection Regulation (GDPR). To conclude, we have no ethical violation in the collection and interpretation of data in our study.

[12] KyungHyun Cho, Bart van Merrienboer, Dzmitry Bahdanau, and Yoshua Bengio. 2018. A scalable neural network language model with global semantic alignment. In Proc. 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT). ACL, 4711–4716.

[13] Allan E Aiello, Audrey Renson, and Paul N Zivich. 2020. Social media- and internet-based disease surveillance for public health. Annual Review of Public Health 41, 1 (2020), 101–118.

[14] Emily Chen, Kristina Lerman, and Emilio Ferrara. 2020. Tracking social media and Twitter Developer Agreement and Policy and related policies. Our release of the dataset is also compliant with General Data Protection Regulation (GDPR). To conclude, we have no ethical violation in the collection and interpretation of data in our study.
[40] Neha Puri, Eric A Coomes, Hourmazd Haghbayan, and Keith Gunaratne. 2020. Social media and vaccine hesitancy: New updates for the era of COVID-19 and globalized infectious diseases. *Human vaccines & immunotherapeutics* 16, 11 (2020), 2586–2593.

[41] Susan M Sherman, Louise E Smith, Julius Sim, Richard Amlot, Megan Cutts, Hannah Dasch, G James Rubin, and Nick Sevdalis. 2021. COVID-19 vaccination intention in the UK: Results from the COVID-19 vaccination acceptability study (CoVAccS), a nationally representative cross-sectional survey. *Human Vaccines & Immunotherapeutics* 17, 6 (2021), 1612–1621.

[42] Jay J Van Bavel, Katherine Baicker, Paulo S Boggio, Valerio Capraro, Aleksandra Cichovska, Maia Cikara, Molly J Crockett, Alia J Crum, Karen M Douglas, James N Druckman, et al. 2020. Using social and behavioural science to support COVID-19 pandemic response. *Nature Human Behaviour* 4, 5 (2020), 460–471.

[43] Petar Velickovic, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. 2018. Graph Attention Networks. In *Proc. 2018 International Conference on Learning Representations (ICLR)*. OpenReview.net.

[44] Mark D Wilkinson, Michel Dumontier, IJsbrand Jan Aalbersberg, Gabrielle Appleton, Myles Axtom, Arie Baak, Niklas Blomberg, Jan-Willem Bonten, Luiz Bonino da Silva Santos, Philip E Bourne, et al. 2016. The FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data* 3, 1 (2016), 1–9.

[45] Kumanan Wilson, Katherine Atkinson, and Shelley Deeks. 2014. Opportunities for utilizing new technologies to increase vaccine confidence. *Expert Review of Vaccines* 13, 8 (2014), 969–977.

[46] Lingyun Zhao, Lin Li, Xinhao Zheng, and Jianwei Zhang. 2021. A BERT based sentiment analysis and key entity detection approach for online financial texts. In *Proc. 2021 IEEE International Conference on Computer Supported Cooperative Work in Design (CSCWD)*. IEEE, 1233–1238.

[47] Jiong Zhu, Yujun Yan, Lingxiao Zhao, Mark Heimann, Leman Akoglu, and Danai Koutra. 2020. Beyond homophily in graph neural networks: Current limitations and effective designs. In *Proc. 2020 Annual Conference on Neural Information Processing Systems (NeurIPS)*, Vol. 33. NeurIPS, virtual, 7793–7804.
Table 6: Diffused information themes and examples.

| Theme                        | Description                                                                 | Example (Translated to English)                                                                 |
|------------------------------|-----------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|
| Positive news                | Positive news about vaccines & vaccination                                   | Pfizer/BioNTech’s vaccine would be effective against the new British variant of COVID19.       |
| Negative news                | Negative news about vaccines & vaccination                                    | Portugal: She dies 2 days after the vaccine (at 41 years old). Her family asks for explanations |
| Distrust in government man-  | Doubt about the trustworthiness of governments or medical institutions, e.g.,  | They have lied to us so much about masks, chloroquine, contagion in children, that it will be   |
| agement                      | regarding the daily update of statistics                                      | difficult to trust them the day they will tell us about a harmless vaccine.                     |
| Dissatisfaction with politics/policies | Unsatisfactory views of politics/policies, such as ineffective vaccination programs. | I am opposed to mandatory vaccination because all of the world’s health organizations say that it is not the right way for a vaccine to spread. |
| Perception of the pharmaceu-  | Perception that pharmaceutical manufacturers pursue only economic interests    | Pfizer’s CEO sold 60 percent of his shares when the Covid vaccine was announced. When the CEO    |
| tical industry               | rather than public health interests                                           | sells, it stinks                                                                             |
| Conspiracy                   | Content that describes the event as the secret acts of a powerful, malevolent | 18 months they’ve been on the vaccine ???? When did they know there would be a Covid 19 "pandemic" ???? |
| Beliefs, attitudes about health and prevention | Personal views on vaccines and the immune system, e.g. homeopathy, natural immunity, alternative therapies. | There is no point in a generalized vaccine for a disease whose mortality is close to 0.05%. |
| Positive personal expression | Personal expression of positive attitude towards vaccines                     | We have a new weapon against the virus: the vaccine. Hold together, again.                    |
| Negative personal expression | Personal expression of negative attitude towards vaccines                     | Why could actually 1.5 billion Chinese get healthy without vaccination, and with us it only works with vaccination...? |
| Positive information         | Positive expressions about vaccines from healthcare professionals            | #COVID19 #vaccinationHow does an mRNA vaccine work?                                            |
| Negative information         | Negative expressions about vaccines from healthcare professionals            | My daughter, a nurse at the AP-HP, on the vaccine ‘Ah ah ah! They don’t even dream about it, they start with the old ones so that we can attribute the side effects to age’. |